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AI Integration

Scaling AI for business model innovation

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Abstract

Artificial Intelligence (AI) is still largely unexplored within information systems research, and most published work remains non-academic (Collins et al., 2021). While there exists some research related to the challenges incumbent organizations have to scale AI, there is little insight to why some succeed. The paper applies a multidimensional framework called the Artificial Intelligence Innovation Maturity Index (AIMI) (Yams et al. (2020) to analyze six AI deployments in European organizations. The purpose of the study was to identify success factors and assess organizations' maturity to integrate AI for business model innovation. The study conducts a qualitative approach where 7 respondents were interviewed regarding an implemented AI use case. The paper contributes with practical advice to managers of what to consider when leading and investing in AI. The findings indicate that the primary investment focus is dependent on the organization's AI maturity level and considers a short term and long term purpose. The paper contributes to research formation related to applied artificial intelligence, digital transformation, maturity models and business model innovation.

Keywords

artificial intelligence, data-driven, business model innovation, digital transformation, digital maturity, AI maturity

Foreword/ Acknowledgements

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1. Introduction

1.1 Background

Digitalization of society is making the global business environment more complex. It brings a speed to change, where organizational agility, decision-making ability and business models innovation are vital elements to an organization's long term competitiveness (Sharda et al., 2014; Vachhrajani, 2021; Iansiti and Lakhani, 2020). Digitalization, referred to as “the way many domains of social life are restructured around digital communication and media infrastructure” (Brennen and Kreiss, 2016) can simply be described as the way that society reacts and reshapes itself around digitization.

Digitization is the ability of converting hardware into digital bits (Loebbecke & Picot, 2015). Digitization has enabled new ways of communication, collaboration and interaction between humans, between humans and machines and between machines. Moreover, these different types of interactions generate large amounts of information, referred to as “data”. Digitization has enabled a way to collect and store data, which has provided opportunities for analyzing and using data for business purposes (Loebbecke & Picot, 2015, Grover, 2018). The application of data analytics has evolved over time, causing an ongoing societal digital transformation, which affects organizations of all sizes and a need for reshaping their business models (Davenport,2020, Loebbecke & Picot, 2015).

Business models represent the link between strategy and the organization. It describes the goal for how to generate profit by creating and capturing value for different stakeholders (Ricart, 2020; Iansiti & Lakhani, 2020). The operating model, on the other hand, describes how value is delivered to stakeholders at economies of scale, scope and learning.

Compared to traditional organizations, digitally born organizations have a foundational different structure of value creation, capture and delivery. Traditional organizations often struggle to adapt to market changes caused by new technology, coined as “the *incumbents curse” by* Chandy and Tellis (2000). An incumbent organization is a well established organization in a specific market or industry (Oxford University Press, 2020; Crittenden et al., 2019). Because of its status, it has the necessary resources to dominate the market today. However, it is limited by its operating model and previous infrastructural investments, to swiftly adapt its operations to new conditions on the market (Chandy and Tellis, 2000; Crittenden et al., 2019).

Traditionally, operating models have connected stakeholders through a fairly straightforward process and pricing mechanism. Today, incumbent firms are colliding with software-centric and data-driven operating models. In a fully digitized business, the options are broader because value creation and capture can be separated more easily and come from different stakeholders at the same time.

What makes digital operating models special is that they can leverage network and learning effects. Network effects symbolize that the underlying value of a product or service increases as the number of users for that product or service grows. The more connections in the network, the greater the value and possible match between users. Similarly, learning effects can add value to existing network effects or generate their own value. By training and optimizing the algorithm with larger volumes of data, the more accurate the output will be and the more complex problems it will be able to solve. The larger the network, the greater the value of the connections, the greater data flow, the greater opportunities for AI and learning overall (Iansiti & Lakhani, 2020).

These highly-scalable operating models are leveraging Artificial Intelligence (AI) technology to drive personalization and expand the scope of available services on the market (Iansiti & Lakhani, 2020). What makes AI valuable is the power it has to process large data sets, commonly known as “big data”, at an extremely fast pace compared with humans cognitive abilities to process information (Iansiti & Lakhani, 2020; Sharda et al., 2014; Loebbecke & Picot, 2015).

Applied AI such as data science or machine learning methods is changing value creation, capture and delivery, which impacts market structure and competition. It affects industries and organizations of all sizes and transforms many job functions such as recruiting, sales, manufacturing, and agriculture. AI can e.g. prioritize sales leads, automate visual inspection of products, optimize recruiting funnels or increase crop yields through precision agriculture (Iansiti & Lakhani, 2020; Ng, 2022). It suggests a convergence of humans and machines (Van Rijmenam, 2020). Tasks that were traditionally allocated to human employees such as painting, pricing goods, service recommendations or qualifying loan applications are now shifted to powerful algorithms (Iansiti & Lakhani, 2020),

It falls on managers to communicate, lead, coordinate and control organizational efforts related to AI. The reallocation of workforce tasks, from human to machine, provides new challenges for leaders to manage. Some are technical, such as finding effective solutions for human interaction, overcoming trust, safety and security issues or avoiding negative consequences of AI application. Other challenges are social, involving morals and ethics related to workforce and consumer privacy, fairness, justice, discrimination, bias, deskilling or surveillance. This suggests a need for augmented leadership capabilities and mindset (Berente et al., 2021; Iansiti & Lakhani, 2020; Canals & Heukamp, 2020; Pfeffer, 2020; Heukamp, 2020; Ricart, 2020). Berente et al. (2021) suggest that the information systems field can contribute with information about the AI phenomenon, AI problems and solutions to managing AI to other fields, such as management and computer science, because it addresses both social and technical aspects.

AI is already driving explosive growth for organizations such as Facebook, Tencent, Alphabet (Google), Walmart, Microsoft and Ant Financial by integrating AI with core business processes. Through AI integration, organizations such as these, keep outperforming incumbents on a financial and operational level by facilitating radical business model innovation cutting across various sectors (Iansiti & Lakhani, 2020; Marr, 2019).

In comparison, many incumbent organizations have yet to realize the full value of their AI investments. Many big data projects have provided disappointing results, failed to go beyond piloting and experimentation, and have been abandoned (Iansiti & Lakhani, 2020, Grover et al., 2018, Loebbecke & Picot (2015)).

Loebbecke & Picot (2015) suggest that incumbents struggle to adapt their business models, because they fail to adapt to and embrace opportunities that come with digitization and big data analytics. Moreover, incumbents tend to get stuck while trying to prove business value of AI application (Iansiti & Lakhani, 2020; Fountain - Jones, 2019). Fountain - Jones (2019) further suggests that organizations have failed because they have focused on specific AI technologies, data collection or investing in sensors or storage solutions before clarifying what business purpose or problem that data is supposed to solve with AI. Furthermore, the few incumbents that manage to scale AI initiatives tend to target their efforts towards turning *existing* internal processes more efficient, rather than *new* business opportunities (Fountain - Jones, 2019).

Currently, there is an intense competition surrounding AI worldwide. On a global level, American and Chinese organizations lead AI research, development, patents, and application, followed by the European Union (EU). A key characteristic of EU's way to AI is a strong ethical framework, which encourages European companies to invest in AI based on European values and concern for data privacy (Annoni et al., 2018).

In Sweden, the government's goal is to make Sweden a leader in harnessing opportunities that AI can offer, with an aim to strengthen Sweden's welfare and competitiveness (Ministry of Enterprise and Innovation, 2018). Therefore, it is important for Swedish organizations to take AI integration into consideration when strategizing for long-term profitability, to remain competitive on a global market.

1.2 Purpose and Research question

There is already some research related to the challenges why incumbent organizations fail to scale AI, but little insight to why some succeed. Therefore, the paper aims to compare and analyze a number of deployed AI use cases based on a multidimensional framework. The framework, called the "AI innovation maturity index framework" highlights six dimensions of enabling AI for business model innovation. The paper aims to identify which of these dimensions were vital for scaling AI use cases in the organization and provide a prioritization of these elements towards further AI integration.

The paper's hypothesis is that if the experienced risk for companies to invest in AI initiatives is lowered, organizations will want to integrate AI with core business models. The paper assumes that, by understanding which elements to prioritize investments in, the experienced risk can be lowered and generate a willingness of scaling AI. The paper aims to create a roadmap for how managers of incumbent organizations can act to realize and motivate AI investments. The focus of the paper is to address what incumbent organizations should prioritize to increase AI maturity. The paper investigates this matter through the research question:

Which prerequisites are vital for organizations when integrating AI for business model innovation?

Table 1 lists the abbreviations, further used in the paper

AI	Artificial intelligence
AIMI	AI Innovation Maturity Index
EU	European Union
ML	Machine learning
NLP /NLG	Natural Language Processing/Generation
MVP	Minimum Viable Product
POC	Proof of concept
RPA	Robotic Process Automation
R&D	Research & Development

Table 1. List of terms

2. Related work/ Previous research

The related work section presents previous research on the research topic. It begins by providing a brief introduction to business model innovation, followed by three sections dedicated to introducing the AI phenomenon for application and integration within a business context.

2.1 Business model innovation

Organizations can be analyzed based on their values, opportunities, capabilities, and structure. Its values can be identified in a business mission and the product or services the organization offers. The opportunities it has is based on its external environment and what the market values. Capabilities in the form of what the organization does well compared to competitors and the assets and abilities it has to gain competitive advantage. Moreover, organizational and industry structure matters for achieving superior performance on the market (Jared & Michael, 2022).

A business model can be viewed as a reflection of a realized business strategy. It describes the goal for how a business unit creates and captures value for different stakeholders (Günter et al., 2017; Ricart, 2020; Iansiti & Lakhani, 2020). Value creation, often referred to as value proposition, symbolizes the issue the organization solves for its customers and the reason why customers select certain products or services over others. Value capture, on the other hand, symbolizes the margin between the cost of providing a product or service and the revenue, what the customer is willing to pay for it (Iansiti & Lakhani, 2020).

Ricart (2020) proposes three global trends that are shaping business models today. The first trend suggests that business models are largely moving away from product based business models towards service and solutions based business models. These business models are often delivered to customers on a subscription basis, in which customers pay for using a service or solution over time.

The second trend is the growth of ecosystems. In an ecosystem, organizations share value creation and capture over a network of complementary products and services, offered by what traditionally has been separated as suppliers, distributors or customers. Today, competition relies less on *copying* successful business models and more on *replacement* of different business models to cater the same needs. It has opened up a space for exploiting complementary differences and integrating these differences within ecosystems. The ecosystem members can play different roles to each other, purchasing and providing different solutions from and to other members (Ricart, 2020).

The third trend is the creation and use of multi-sided digital platforms. Multi-sided digital platforms have made it possible to integrate and coordinate parts of the ecosystem, creating and coordinating new markets by connecting different user groups (Ricart, 2020).

While the business model describes the goal, the operating model describes how value is delivered to customers at economies of scale, scope and learning. Scale, by delivering as much value to as many customers as possible at the lowest cost. Scope, through the range of products and services a firm can offer. And learning, the operational capability to continuously improve, increase performance and innovation capability (Iansiti & Lakhani, 2020).

Organizations are shaped by their operating model. While it manages complexity and growth to some degree, it limits the organization’s ability to deliver value. When an organization expands, complexity can cause inertia due to bureaucracy, silos, inefficiency, and norms. There are indications that Artificial Intelligence (AI) has already started to transform business models and operative models in a major way and continues to impact organizations of all sizes (Iansiti & Lakhani, 2020).

2.2 AI definition

AI is a broad discipline with the objective to develop machines to act intelligently (Van Rijmenam, 2020; Gil et al., 2020). The European commission refers to AI as any machine or algorithm that is capable of observing its environment and learning to make actions or propose decisions, based on the knowledge and experience it has gained (Annoni et al., 2018). The EU classifies AI into two parts, core and transversal AI. Within Core AI lies tasks such as reasoning, planning, learning, communication and perception. Transversal tasks include integration and interaction, services, ethics, and philosophy. Within each domain, there are subdomains depending on current application opportunities. The AI taxonomy is illustrated in figure 1 (Annoni et al., 2018)

	AI taxonomy	
	AI domain	**AI subdomain**
Core	**Reasoning**	Knowledge representation
		Automated reasoning
		Common sense reasoning
	Planning	Planning and Scheduling
		Searching
		Optimisation
	Learning	Machine learning
	Communication	Natural language processing
	Perception	Computer vision
		Audio processing
Transversal	**Integration and Interaction**	Multi-agent systems
		Robotics and Automation
		Connected and Automated vehicles
	Services	AI Services
	Ethics and Philosophy	AI Ethics
		Philosophy of AI

Figure 1. AI taxonomy by the European Commission (Annoni et al., 2018)

There is a trend of defining AI on its capabilities rather than what it is. Collins et al. (2021) suggest that it is important for business value research to provide exact definitions on what type of AI application is studied, the choice of theory used and the context in which specific technology is deployed. Berente et al. (2021) further suggests that the AI phenomenon is not a single thing or a set of technologies, a device, a program or an algorithm. AI is rather an idea of an evolving process, rather than a phenomenon in itself.

There is prior work on value creation from the data analytics/business intelligence field that can be helpful to understand how AI solutions create value for business. Davenport (2018) divides the evolution of applied analytics into four eras, where AI belong to the two latest and most advanced. Analytics 4.0 is an era where organizations have reached a level of adopting AI-technologies on a wider scale.

However, while AI has similarities and connections to data/business analytics, it is also different. The mission is similar, as both areas leverage data, employ advanced technology, analysis tools, and use advanced statistical methods to realize business value. However, while some AI solutions are based on statistical methods, there are other AI solutions which are not, such as Natural Language Generation, Robotic Process Automation (RPA) and Rule-based Systems. Moreover, traditional business intelligence relies on descriptive analytics, i.e. analyzing what has happened and why. More advanced analytics, such as predictive and prescriptive analytics, i.e. predicting what will happen and suggesting what to do about it, relies on solutions provided by data mining and artificial neural network methods (Dearborn, 2015; Berndtsson et al., 2020; Davenport, 2018).

AI terminology can be confusing and misleading. An example of that is Deep learning, which is a commonly used term for artificial neural networks. Simply put, Deep learning takes an input (A), e.g. different factors to estimate a price of a house, and provides an output (B), e.g. an estimated price of the house. It is a piece of software which uses a mathematical equation to calculate given inputs (A) to provide (B), a calculation of the input (Ng, 2022). Deep learning has provided many recent advances in AI, such as the ability for computers to scan and recognize what or who is in an image or video. But also to understand written texts and spoken words, called natural language processing (NLP) (Marr, 2019).

The most prominent research within AI has surrounded machine learning (Collins et al., 2021). Machine learning (ML) offers computers an ability to learn without being programmed. Basic machine learning is predictive analytics, which aims to provide scenarios of insight to what could happen given different circumstances. It uses data mining techniques to train models with known data to estimate potential future situations with new, unknown data (Davenport, 2018, Dearborn, 2015)

A machine learning model can be trained in various ways. A common training method is called “Supervised learning”. It basically means that a programmer provides an ML model with pre-labeled data, e.g.1000 pictures of cats named “cat”. Next time the model receives a new picture, it can recognize similar features in the photo and further know that it should classify it as a cat, instead of a dog, for instance (Collins et al., 2021). Another training method is to let the ML model figure out interesting patterns by itself, by using “unsupervised learning”. Unsupervised learning practically means that a programmer provides the ML model with unlabeled data. The ML model then proceeds to identify features and categorizes patterns by itself, e.g. it could group pictures of dogs, cats and giraffes together, supposedly because of their similar features as animals. However, using unsupervised learning means that the model cannot describe the context of what it has found and must be interpreted by a human (Collins et al., 2021). Reinforcement learning is a third training method, which teaches an ML model if the output is right or wrong based on set criteria by awarding it with high, positive numbers or punishing it with low, negative numbers. The model will learn what is a right or wrong output and adjust thereafter (Ng, 2022; Iansiti & Lakhani, 2020).

An ML model is generally tested with a validation dataset, for which the predicted outcome is compared to the known outcome. When a model can explain the variance in the training data and predict according to a set criteria, it can be deployed to predict or classify new data for which the outcome variable is unknown (Davenport, 2018). ML projects often result in a running AI system. In contrast to machine learning, “data science” extracts knowledge and insights from data. The output of a data science project is often a report that summarizes conclusions for executives to take action on, or for a product team to decide how to improve a website. Additionally, graphical models and knowledge graphs are other tools for training AI systems to make computers act intelligently (Ng, 2022).

While there is still a debate about the definition of AI, it is generally divided in two parts, general (strong AI) and narrow (weak AI) (Iansiti & Lakhani, 2020; Gil et al., 2020). General (strong) AI is a hypothetical type of AI, which indicates a system that cannot be detected as “Non-human”. General AI aims to meet human-level intelligence to apply problem-solving ability to any type of problem, just like a human brain. General AI has yet to be developed, and experts argue whether it will ever be possible to reach that level (Gil et al., 2020).

In comparison, Narrow (weak) AI describes AI methods that are applied to solve a defined problem and to perform a specific task in a single application domain. Such as finding patterns in big data and acting upon it in an autonomous and automatic way (Van Rijmenam, 2020; Gil et al., 2020).

In this paper, we have chosen to base our definition of AI according to the European commission taxonomy of AI (Annoni et al., 2018). The paper will further explore what is referred to as narrow (weak) AI which is described by Van Rijmenam (2020) and Gil et al., (2020) as methods applied to solve a defined problem and performing a specific task in a single application domain in an autonomous and automatic way.

2.3 AI Application

After deployment of an AI model, the model learns in the context of a specific task. It cannot learn other tasks on its own or apply it to different domains by itself (Gil et al., 2020). However, due to recent, significant advances in AI, applied AI is beginning to move from a “narrow” state towards a more broad era where AI technologies can be applied to tasks across multiple domains and problem sets (Gil et al., 2020).

Yams et al. (2020) suggest a division between two focus areas for AI application. The first area suggests a focus on efficiency, referred to as "Bolt-on” application. It indicates solutions designed for *existing* processes and products with a specific focus on optimization, risk management, and short-term return on investments. This type of application primarily enables *incremental* innovation of *existing* business models. While narrow, “bolt-on” application of AI can lead to improvements in specific areas, recent research suggests that a broad, multidimensional integration of AI in the organization can lead to long-run competitive advantage, innovation capability and increased profitability (Yams et al., 2020; Haefner et al., 2020).

The second area therefore focuses on AI application for innovation, referred to as "Integrated AI”. Integrated AI considers an organization's core domain area and becomes deeply integrated with the overall organizational purpose and strategy. It augments and transforms the organization at its core and suggests a more *radical* innovation focus, where tasks previously dedicated to humans are shifted to algorithms (Yams et al., 2020). AI integration suggests going beyond simple automatization of a business model, or modular changes to it and can radically change business model governance, the capabilities needed in the organization and the value proposition to customers (Ricart, 2020).

Exploring AI applications can lead to reinvention of business models or a complete transformation of the business approach (Marr, 2019). AI technologies process data, which can create new value propositions and facilitate business model transformation through interaction. AI-based business models can support business activities in a more efficient way by analyzing, remembering large data quantities or discovering new patterns (Ricart, 2020).

Mohanty & Vyas (2018) describe AI as intelligent systems which process information to do something purposeful and seek the best plan of action to accomplish assigned goals. These systems can have either assisting, augmenting or autonomous capabilities. Assisting capabilities focus on improving the day-to-day activities that people and organizations are already doing. Augmented intelligence provides complementary capabilities to do tasks that humans cannot do on their own. Furthermore, autonomous capabilities create and deploy machines that are intelligent and adaptive to act on their own, without human involvement.

Zamora (2020) proposes four areas where AI can be useful. Firstly, AI can be used to automate and re-design processes by removing manual steps, leading to increased efficiency and reduced cost. Secondly, AI can be used for anticipation, meaning the use of data to predict and recommend. Further, AI can be used for improved coordination, by using AI to coordinate multiple actors at the same time. Lastly, AI can be used for personalization, to customize products and services for individual preferences.

Moving forward to AI use cases. An AI use case is a set of activities designed to reach a specific goal from a business or customer perspective, where one or more AI solutions are used (Applied AI, 2022). Marr (2019) suggests three main use cases for AI in business. Firstly, AI can change the way the business understands and interacts with customers, understanding which products and services that customers want, predicting market trends or providing personalized interactions. Secondly, AI can offer more intelligent products and services to customers. Thirdly, AI can improve and automate business processes through e.g. medical diagnosis, food quality checks, autonomous drones, automated fulfillment centers or delivery robots.

Davenport (2018) suggests three areas of capabilities that AI can provide to business activities. The first is for automating structured and repetitive work processes, e.g., via robotics or robotic process automation (RPA). The second is cognitive insight, gaining insight through analysis of structured data, e.g., by using ML. Thirdly, by cognitive engagement, i.e. engaging with customers and employees, via NLP chatbots, intelligent agents and ML.

Hofman et al. (2020) propose four AI solution types. Firstly, AI rule-based solutions (e.g. robotic process automation), which are useful for automating standardized project tasks via simple workflow integration. Secondly, AI-enabled solutions (e.g. Chatbots consist of human-computer-interaction, based on Natural language processing (NLP). Thirdly, AI -based solutions (e.g. budget estimation or risk advice, support processing core tasks creating new knowledge and lastly, full AI solutions (e.g. chatbot which communicates AI based budget estimations, use AI for input and output as well as task processing (Hofman et al., 2020).

Deploying AI can lead to business process improvement, product and service innovation, improved customer experience, market enhancement and organizational performance. Additionally, deploying AI solutions can create symbolic value, such as a positive business image and reputation (Grover et al. 2018).

Big data can be a source of innovative products, services and business opportunities and organizations which use it to guide strategies and day to day operations perform better financially (McAfee & Brynjolfsson, 2012; Lavalle et al., 2011). A survey made by Deloitte in 2017 revealed that the most common objective for using cognitive capabilities, such as AI, was to enhance existing products and services as well as creating new products and pursuing new markets (Davenport, 2018).

In a study conducted by Lavalle et al. (2011) the authors found that top-performing organizations used analytics five times more than lower performers and had a widespread belief that analytics offers value. Moreover, in a 2017 Genpact-sponsored survey of 300 global executives, more than 40% of leaders said that AI already improves customer experience and that they were twice as likely to achieve increased revenues from AI. A survey conducted by Teradata found that the most common areas for driving revenue from AI investment were product innovation, customer service, supply chain and operations (Davenport, 2018).

Moreover, McAfee & Brynjolfsson (2012) found that leaders who considered their organizations to adopt a higher degree of data-driven processes were more productive and profitable than competitors. Furthermore, data-driven organizations grow about 30% on average annually and are more likely to acquire and retain customers (Vachhrajani, 2021).

2.4 AI Integration

An AI integrated organization is built around smart algorithms that define processes, deliver customer services, and act when necessary. The AI solutions become the intellect, the interoperability, the connection and the exchange between consumers, things, processes and information that define business value. Over time, the algorithms learn to understand user and device behavior, to perform the right actions accordingly, to optimize a supply-chain, drive cars, monitor robots or determine marketing messages. Integrated AI sets the groundwork for transformational or radical innovation. It is strategic, long-term oriented and focuses on organizations' wider ecosystems with an aim to create value across a broad market (Van Rijmenam (2020), Yams et al. (2020).

Iansiti and Lakhani (2020) visualizes AI integration as an “AI factory”. The AI factory is a scalable “decision engine” which powers digital operating models and increasingly embedded managerial decisions in software. It treats decision-making as an industrial process and digitizes tasks that traditionally have been acted upon by human employees. Such as approving loans, setting prices, or allocating the closest car to pick up a passenger.

The AI factory infrastructure consists of four components visualized in Figure 2; the Data pipeline, algorithm development, an experimentation platform and software infrastructure (Iansiti & Lakhani, 2020).

The first component, the Data pipeline, represents a systematic, sustainable and scalable process which includes data gathering, cleaning, normalizing, integration, processing and safeguarding data from bias and errors.

The second component, algorithm development, is what makes data useful. An algorithm describes a set of rules a machine follows to make decisions, generate a prediction or solve a problem based on data input. The majority of production-ready and operational AI systems today use machine learning.

The third component of the AI factory is the experimentation platform. The platform represents the mechanism which tests an AI model’s predictions and decisions to ensure that they have the intended effect.

Lastly, the software infrastructure embeds the data pipeline in software and computing infrastructure and connects internal and external users to the AI factory (Iansiti & Lakhani, 2020)

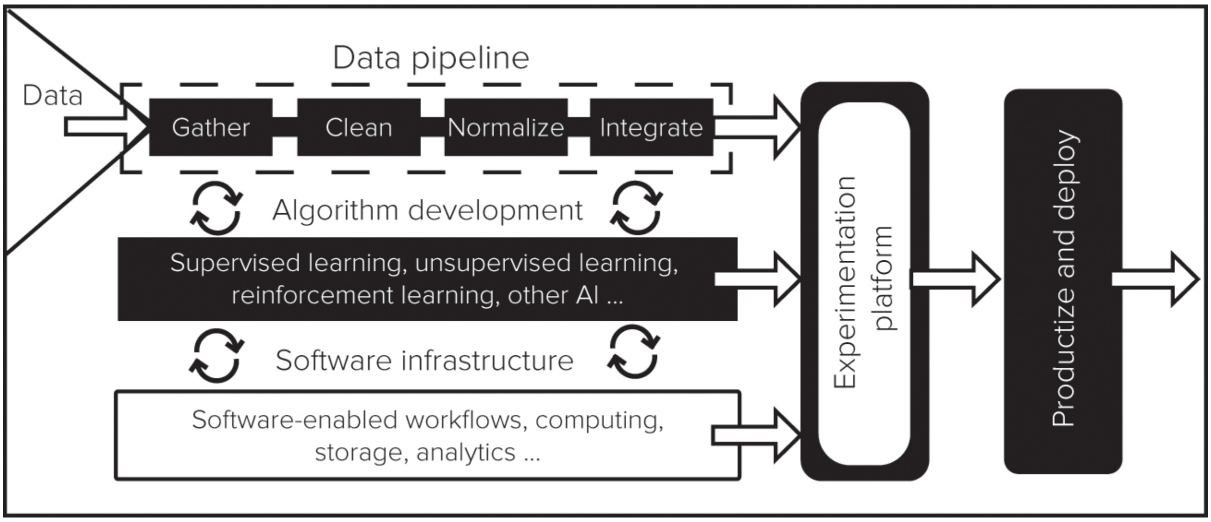

Figure 2. AI factory components (Iansiti & Lakhani, 2020)

Using analytics will turn internal and external data into predictions, insights and choices which can automate a variety of operational actions. Some digital operating models only manage information flows, while others guide how the organization builds, delivers or operates physical products. The main difference between traditional and digital operating models is that AI factories are at the core of the model, guiding the most critical processes and operating decisions, while humans are moved off the critical path of value delivery.

This process can be envisioned as a virtuous cycle between user engagement, data collection, algorithm design, prediction and improvement, which continue to reinforce each other. More data makes better, more accurate algorithms, which generates better services and more value to users, which creates more incentive for usage, which in turn provides more data for the algorithm to explore and train with. This reinforcing process is illustrated in figure 3. An example of this is how a search engine processes data to figure out common search patterns, which in turn improves the service and motivates users to continue using the service (Iansiti & Lakhani, 2020).

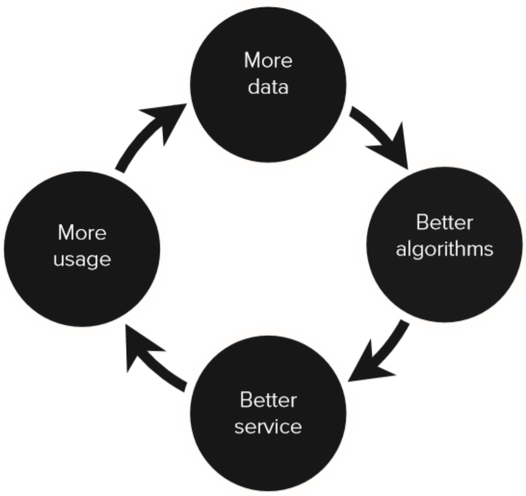

Figure 3. The AI factory's virtuous cycle (Iansiti & Lakhani, 2020).

Moreover, by integrating AI with the core business, the operating model can provide higher levels of scalability, achieve a broader scope and reach a higher learning rate, because the critical path to value delivery has changed (Iansiti & Lakhani, 2020). As a consequence of AI integration, organizations are faced with choices of which capabilities to invest in, whether to outsource or develop AI skills in-house and which platform and tools to use (Gil et al., 2020).

Examples of organizations that have integrated AI include Google, Amazon, and Baidu, whose competitive advantage derives from AI and the associated "virtuous circle of data". Their virtuous circle of data reinforces existing business models and creates opportunities for further business innovation. Moreover, they don't just have structures, processes and technologies and organize their operations around AI, they are also driven by a sense of purpose and strategic alignment of AI investments (Yams et al., 2020).

Yams et al., (2020) suggest that the full potential of AI will only be reached by organizations in the higher maturity stages. Since those organizations have an innovative culture and flexible organizational structures that more fully merge with AI across the organization.

Firstly, AI integration can democratize and distribute innovation across the organization, instead of centralizing it within a specific function or department. By automating routine tasks with AI, more time can be dedicated towards innovation focused tasks. Moreover, by building a data-driven organization, AI-supported systems enable employees with more informed decision-making (Yams et al.2020).

Secondly, AI integration can increase diversity and cross-functional collaboration by breaking down organizational silos and enabling diverse talent recruitment and team formation, inside and outside the organizational boundaries. A recommendation system could e.g. assess innovation potential of external partners from a wider ecosystem, to optimize investments in external collaborations (Yams et al.2020).

Thirdly, AI integration can increase organizational capacity for radical innovation by sensing opportunities. Moving from a reactive to a proactive mindset. AI-supported predictions can make the organization aware of changes in stakeholder behavior and macro trends, which enables the organization to identify future needs in a more accurate way than before (Yams et al.2020).

Lastly, AI integration can support the development of a learning organization. By personalizing learning paths adjusted to the needs, preferences and learning styles of individual employees, it can generate creativity and a desire for learning. For example, by applying AI for automated note-taking, a recommendation system can share knowledge that is relevant and interesting for employees on an individual level. However, Yams et al.(2020) argue that a more broadly developed learning organization enabled by AI can happen when AI is embedded and interlinked with innovation, together with adopting a data-driven learning mindset and organizational culture (Yams et al. 2020).

3. Conceptual framework

The conceptual framework constitutes the lens for studying the research question. The core of the conceptual framework consists of the AI Innovation Maturity Index, developed by Yams et al., (2020) and is supported by related research on the topic.

3.1 Maturity Models

Maturity models are tools for identifying an organizations' present state and serve as a guiding tool for how to grow and enhance the ability of achieving a certain task. To support IT management, over a hundred maturity models have been developed during the last decade (Becker, Knackstedt & Pöppelbuß, 2009). When management develops roadmaps for digital transformation, digital maturity models are often used to assist the process of validating which activities to conduct and prioritize to reach a higher maturity level (Teichert, 2019).

Further, there are question marks when it comes to clarification and validation of maturity models. Two general criticisms are frequently mentioned. Firstly, a coherent understanding of which the most common maturity dimensions are is not clarified. Secondly, various maturity models are too general for applying and providing specific guidelines to different industries on their respective digital maturity journey (Teichert, 2019).

Another dilemma of using maturity models is that there is no common definition of the concepts digital maturity and digital transformation, which emphasize the importance of research on these topics (Teichert, 2019). Furthermore, research of artificial intelligence and organizations' maturity level related to AI is even less, and specific AI maturity models have primarily been developed by practitioners rather than academia (Yams et al., 2020).

Despite these criticisms, the paper believes that maturity models can be helpful for organizations in their development towards increased digitalization and trustworthy integrated AI. Maturity models can provide organizations with an indication of their current degree of maturity and be used as a tool for making business decisions and investments within these areas. Moreover, maturity models can provide an indication of how other, more advanced companies within these areas conduct their business. Those models can also provide indications of what is possible to achieve with different circumstances. Additionally, it can indicate which possible actions are reasonable and feasible during the organization's current conditions.

Lastly, it is important to avoid overconfidence in a maturity model's recommendations. The recommendations provided by models should rather be seen as a suggested direction to investigate further and gain an overview of potential investment areas to move forward with.

3.2 The AI Innovation Maturity Index

The AI innovation maturity index (AIMI) is a framework that aims to guide organizations in their maturity journey towards trustworthy integrated AI. The framework is based on a collection of frameworks to gain a better understanding of companies' AI maturity level and their current conditions of implementing AI solutions for innovation. While there are previous frameworks describing specific aspects of integration of AI, they lack a multidimensional and integrated perspective (Yams et al., 2020). Earlier frameworks tend to focus on either strategic, organizational aspects or technical aspects separately. The aim of the AIMI framework is to combine organizational, technical and strategic aspects to visualize the organization's AI innovation maturity and thereby obtain guidance about the organization's starting point towards trustworthy integrated AI (Yams et al., 2020).

The AIMI framework explores and aims to guide companies in their journey towards integrated AI for business model innovation, by investigating individual dimensions related to AI in relation to other dimensions. While assessing the organization’s current AI maturity, the authors suggest that the framework can help to deal with the complexity that comes with digital transformation enabled by AI, to gain an overall idea of which capabilities to invest in. The authors indicate that the framework can be used to support integration of AI with organizations' innovation management systems, to strengthen organizations’ capability for innovation (Yams et al., 2020).

Current research lacks a systematic overview of how AI can support different elements of innovation management (Yams et al., 2020). Therefore, Yams et al. (2020) suggests that organizations can benefit from taking a multidimensional and integrative approach to AI. This approach could mean gaining an overview of their AI portfolio and integrating a specific AI strategy with their general business strategy, to be able to invest in and coordinate the prerequisites of reaching a higher AI maturity (Yams et al., 2020).

To enable and accelerate innovation in organizations, the AIMI framework intends to be used as a compass, map, and tool. It illustrates which aspects organizations need to develop and what types of support to engage with at different stages of maturity to derive the most value. The framework offers suggestions on how AI can be used in various ways as an innovation enabler, moving organizations from incremental towards more radical innovation (Yams et al., 2020)

3.2.1 Stages of AI maturity

The AIMI framework proposes 5 stages of AI maturity: Foundational, experimenting, operational, inquiring and integrated (Yams et al., 2020). Yams et al., (2020) suggest that organizations need to move towards the Inquiring and Integrated stages in order to start increasing incremental innovation and strengthening the organizational capacity for more radical innovation enabled by AI. The result of increasing AI maturity can lead to AI-driven innovation and new innovative business models, based on distributed decision-making and supported by new ways of organizing.

Foundational

At this stage, the organization lacks AI competence and the understanding of what AI can do is limited. AI specific processes or budgets do not exist. The organization may have some interest in AI, but not enough knowledge, which hinders the organization from making decisions of which applications and use cases are relevant based on the organization's needs. The organization has a short-term mindset related to AI investments, and the focus of the investments is to generate efficiency gains through “bolt-on” use cases and direct return on investment.

Experimenting
At this stage, the organization is building capabilities to execute on more straight-forward AI applications. This is an “action” stage where the focus is on a few specific projects, based on identified internal needs. It includes building technical capabilities such as discovering, cleaning, and making use of any current organizational data, in addition to instrumenting existing systems to collect more quality data. Moreover, it includes building people capabilities such as hiring, training and developing an experimental mindset.

Operational
At the operational Stage, the organization has a few scaled AI use cases and a technical and organizational capacity to keep them going. It is starting to reap benefits of a built-up knowledge and capacity around AI to create new applications with higher speed. The organization has sufficient internal analytics and quality data. Which can be applied to multiple use cases, and tend to move from a business optimization approach to an outward and forward-looking innovation strategy and mindset. At this stage, the organization is gaining awareness and increasingly engaging with its external ecosystem.

Inquiring
At the inquiring stage, the organization is doing a major shift in the leadership mindset and a more strategic orientation takes place. The organization has understood that AI is not just a technology, but rather the basis for larger organization, market and industry transformation. The organization’s further exploration of AI’s impact on business strategy and innovation-based products gains momentum and becomes more external- and future-facing in regard to its ecosystem and R&D. Structurally, the business may be moving towards self-organized, flexible teams, driven by a common sense of purpose.

Integrated
Organizations such as Google, Amazon and Baidu are some of the few organizations which have reached the integrated stage. In this stage, organizations whose competitive advantage derives from AI and its “virtuous circle of data " reinforces existing business and creates possibilities for further business innovation and transformation. The enabling structures, processes, technologies, and operations are in place to accelerate AI agility, supported by an understood sense of purpose and strategic alignment centered on value creation and purpose.

3.2.2 Dimensions of the AI Innovation Maturity Index

The framework consists of six main dimensions that are interconnected and interdependent, illustrated in Figure 4; data; strategy, ecosystems; mindsets; organization; technologies. Further, Trustworthy integrated AI is the core component of the index. The dimensions enhance each other cross-functionally and enable a higher maturity for AI innovation in the organization (Yams et al., 2020).

Figure 4. AIMI - AI Innovation Maturity Index (Yams et al., 2020)

3.2.2.1 Data

The data dimension is a key resource for reaching a higher AI maturity and has potential to radically alter business strategy (Yams et al., 2020; Günter et al., 2017). It is an important asset for AI application because it fuels AI algorithms and enables organizations to make data-driven decisions (Yams et al., 2020; Iansiti & Lakhani, 2020).

Data is a unique asset because it has limitless supply, can be reused, integrated and is never really consumed (Lavalle et al., 2011; Vachhrajani, 2021, Grover et al.2018). The value of data is determined by three main characteristics; volume;velocity;variety. Volume, because of the large amount of information which can be generated and collected at each moment. Velocity, because of the speed in which data is created. Variety, because of the various formats it can take, such as text, audio, sensor input and GPS signals (McAfee & Brynjolfsson, 2012).

Algorithms without data are like driving a car without fuel. With larger amounts of qualitative data, the better the algorithms can deliver more precise and valid information to base decisions on (Yams et al., 2020).

3.2.2.2 Strategy

Birkinshaw (2020) refers to strategy as the choices that executives make about where and how the firm competes, based on its position in a marketplace. This position depends on the value proposition it offers to customers and what differentiates it from competitors, as well as the firm's capabilities and activities to deliver.

The strategy dimension focuses on value creation, governance, organization and vision. The strategy dimension addresses the “why” of implementing AI solutions and the organization's ability to align and integrate AI into the wider business context. When business needs are addressed, is it easier to allocate which primary AI activities the organization should concentrate on (Yams et al., 2020).

One of the most important aspects of strategy is how a key resource is going to affect the business. AI can support or drive strategic changes in business models, such as new approaches to offer existing products and services, ways of going to market, distribution channels or entering new industries. However, many companies are not gaining strategic value from their AI investments (Davenport, 2018). Marr (2019) suggests that loosely experimenting with AI does not deliver the necessary effects on business success (Marr, 2019). An AI strategy can help to address this issue (Davenport, 2020).

An AI strategy starts with establishing an AI vision. An AI vision can be described as high-level goals surrounding application and level of aspiration. An AI strategy describes how to achieve the AI vision. To be effective, an AI strategy should be aligned with the overall strategy of the organization and take organization-specific structures and context into consideration (Gil et.al., 2020; Applied AI, 2022). Davenport (2018) argues that developing an AI strategy requires basic know-how of how cognitive technologies are used in business. Davenport (2018) further suggests that a successful AI strategy should identify strengths, weaknesses, opportunities and threats of using AI. Moreover, it should clarify the organization's ambitions and targets, including setting realistic timelines and a partner strategy. Similarly, Marr (2019) suggests that the starting point for using AI should be an AI and data strategy which identifies the largest strategic opportunities and threats and pinpoints the most impactful applications. Without thinking of strategic questions, firms waste money and time on cognitive technology. Davenport (2018) further argues that AI strategy should be collaborative and involve some degree of process with a goal to drive educated and informed actions. It can include interviews with internal and external experts, workshops, and strategy review sessions. The outcome may be a series of pilots, proof of concept or production deployments of cognitive tools in different parts of the business (Davenport, 2018).

Compared to startups, which can take advantage of low entry barriers and more easily set up *new* data-driven business models without previous legacy, incumbent organizations have to rethink how data affects *existing* business models. One type of value can be gained from leveraging data for incremental business model innovation, such as deriving insights from analytics to make small adjustments to *existing* processes. The organization continues to function “as usual” but in a more efficient way than previously (Günter et al., 2017).

Moreover, organizations can leverage data to develop *new* value propositions, by targeting a different customer group or interacting with customers in another way to enhance customer experience, trading data or generating insights with other parties. It suggests another, more radical type of business model innovation, where incumbents can use available resources to move from one stage of big data maturity to another. While business model *improvement* vs. business model *innovation* has been a rising discussion topic, there are still few empirical studies of cases where improvements or innovation to business models are based on big data (Günter et al., 2017).

3.2.2.3 Ecosystem

It is nearly impossible for an organization to compete without business partners, stakeholders and collaborators on today's global market. The purpose of an ecosystem is to further strengthen the organization's level of communication, collaboration and impact on the market (Yams et al., 2020).

AI allows the emergence of ecosystems. Larger amounts of data and a more digitized organization needs a larger ecosystem to handle the growing magnitude and complexity of the business. With new ways to organize and coordinate, AI technologies can eg. decrease the cost of group decision-making in platforms, smarter sensing as with (IoT), remembering (big data) and learning (machine learning/deep learning). Improvements on this front allow machines, with human help or autonomously, to learn at a high speed (Ricart, 2020).

The ecosystem enables organizations to share value creation and capture in a network of ecosystem members which offer complementary products and services, traditionally viewed as suppliers, distributors, competitors and customers. Today, competition relies less on *copying* successful business models and more on replacement of *different* business models to cater the same needs. It has opened up a space for exploiting complementary differences and integrating these within ecosystems. The ecosystem members can play different roles to each other, purchasing and providing different solutions from and to other members. Instead of competing, organizations collaborate to gain value by exploiting their complementary differences (Ricart, 2020; Hannah & Eisenhardt, 2018). Furthermore, the creation and use of multi-sided digital platforms has improved integration and coordination of the ecosystem, creating and serving new markets by connecting different user groups (Ricart, 2020).

Successful ecosystems manage to balance competition and cooperation. On one hand, If firms cooperate too much, they may not generate enough profit to survive. On the other hand, if firms compete too much, the ecosystem fails to generate any benefits of collaboration (Hannah & Eisenhardt, 2018). The organization must make a strategic decision about what role it intends to take in a broader ecosystem. E.g. Should the organization take a leading, orchestrating role or should it be an observer, following and adjusting to leaders of the ecosystem (Yams et al., 2020).

3.2.2.4 Mindset

The mindset dimension is closely associated with organizational culture. An innovative and growth mindset promotes the AI aspiration in the organization. Leadership aspects, and the direction and influence it has on the organization, are of importance for this dimension. The framework defines Mindsets as the "mental orientation and intangible capabilities that create the organizational conditions for sustainable development through integration of AI" (Yams et al., 2020).

Vachhrajani (2021) suggests that there is a difference between being data-aware, data-informed, and data-driven. Organizations recognized as "data-driven" actively collect and drive business insights based on analysis of big data. These organizations encourage an organizational culture focused on learning through testing and experimentation (Berndtsson et al., 2007; Dearborn, 2015; Halper & Stodder, 2017). Similarly, Mohanty & Vyas (2018) suggests that AI integration requires a culture of rapid experimentation. By failing fast, the organization will learn and continuously improve. It requires being able to design, develop, conduct tests, exposing prototypes to user experience feedback, testing deployment models, working with cloud partners and other ecosystem players simultaneously.

Heukamp (2020) suggests leaders need to develop traits such as humility, an ability to recognize that in a fast-paced environment of change due to AI, no one will have the answers, and they will need support to find the best solution. Heukamp (2020) suggests that by having an inclusive leadership style, providing transparency, communication and adaptability will be useful to facilitate an environment for AI development, as well as adopting agile development methods (Heukamp, 2020).

A lack of alignment can raise challenges to realize value from big data. The organization can be limited by stakeholder interests, e.g. depending on the purpose of data collection, the organization might not be able to use it for other purposes. Further, a lack of alignment can lead to challenges with integrating AI capabilities with existing organizational structure, which can result in isolated practices, controversies and unclear roles at the operational level. The organization can be limited by a dominant traditional business model, finding it difficult to make sense of the data. Being framed by a traditional business model can be challenging for organizations to sell data-driven propositions to generate revenue from the data. (Günter et al., 2017)

IT-business alignment can be described as a way of ensuring that activities in IT-oriented domains and non-IT domains are coordinated to create new service offerings, increased innovativeness, better business processes and making more informed decisions. This will ultimately lead to an increased value for the overall business (Luftman et al., 2015). By aligning IT investments towards business objectives, firms avoid wasting resources on non-strategic causes (Luftman et al., 2015).

3.2.2.5 Organization

The organization dimension is the tangible, practical part of the mindset, it involves foundational skills, structures, processes and operational aspects of fostering a growth mindset. Additionally, it involves tools for reducing tension in cross-functional or external collaboration and distributed decision-making. It includes hiring, training, and upskilling employees' AI skills and is effectively about how a business can organize for integrating AI (Yams et al., 2020).

AI set new demands on management and leadership capabilities, as decisions are being taken about strategy shifts, technology adoption and organizational change (Heukamp, 2020). AI is coming up with solutions to problems, framing managerial decisions better and making better predictions, which questions the future role of CEOs and senior managers (Canals & Heukamp, 2020). Therefore, Canals & Heukamp (2020) argues that senior managers need to learn about the implications of AI and consider experiences around functionality, possibilities, deployment, and impact.

Heukamp (2020) suggests that there are various competence areas surrounding AI that leaders need to know about, act upon and traits to develop. To be able to leverage the power of AI, leaders need to know about the basics of AI models and the process which generates, collects and analyzes data. Being able to ask the right questions is important, because when leaders make decisions based on output from an AI model, they need to understand the context to interpret the prediction and be aware of potential quality defects and bias, which can have unwanted effects on performance (Heukamp, 2020). Some organizations tend to focus their efforts on data collection before defining a business issue and do not realize there is limited time, energy and resources to explore and understand which areas the data could be useful for, before it loses quality. Defining information gaps first and collecting data later can therefore generate more value for the business (LaValle et al., 2011).

Furthermore, leaders need to develop an ability to judge and learn to improve the quality of decision-making and knowing specific analytics skills to be able to perform and understand analytics. For example, they need to understand the difference between correlation and causality to draw relevant conclusions from data to avoid “black-box” solutions, because algorithms do not have an actual understanding of the real-world (Heukamp, 2020).

Moreover, leaders have to justify their decisions based on the model. Therefore, critical thinking is crucial, to make judgements based on an objective analysis of a problem, questioning relevant criteria, testing assumptions and the quality of the analysis (Heukamp, 2020).

Furthermore, leaders need to know the basics of organizational transformation, developing people and orchestrating business partner collaboration, as they will be in charge of driving organizational change and the impact AI will have on the organization. They will need to grow change management and coaching skills to facilitate interaction between humans and machines to establish a culture of collaboration around AI -driven projects (Heukamp,2020). Furthermore, leaders need to be effective at communicating with decision-makers in non-technical terms, understand key business issues and strategic direction. Moreover, leaders need to develop facilitation and process skills. If a firm consults external experts, it is important to engage the internal management team in the process and the outcome. Moreover, it can be helpful to arrange AI training dedicated for management (Davenport, 2018).

There is a scarcity of AI talent on the market today (Davenport, 2018; Venturebeat, 2021; AI Sweden, 2021). Mohanty & Vyas (2018) suggests that organizations should develop a clear plan of how to attract and retain AI talent, and build the infrastructure and competencies needed, including an AI team of data scientists, data engineers and algorithms. Similarly, Davenport (2018) recommends that firms create a plan for recruiting, evaluating, acquiring, and developing talent, or establishing an ecosystem to augment internal resources. Furthermore, Davenport (2018) suggests it can be helpful for organizations to position AI initiatives as a natural extension of already established analytics capability.

AI talent can be a combination of different skills, such as data sourcing, processing, analytics and algorithmic development and understanding of cloud services. Moreover, it includes skills such as creative thinking, willingness to research and go after unknowns, experimentation, business impact articulation and story-telling (Iansiti and Lakhani, 2020; Mohanty & Vyas, 2018; McAfee & Brynjolfsson, 2021).

At an organizational level, there is a debate about which appropriate organizational model to use for gaining value from big data, and there is little academic literature on how to achieve it in practice. While there are examples of centralized capability structures, it is still unclear how these are put in place, interact with business units or produce value. On the other hand, there are scholars which emphasize the importance of decentralized structures (Günter et al., 2017)

3.2.2.6 Technology

The technology dimension, often referred to as “data infrastructure”, represents the potential for AI development and deployment software. These are the hardware systems, processes and design principles which enable data and analytics. It requires scalability, support of diverse use cases and fast iteration. A strong technology dimension allows for internal data democratization, meaning the ability for less technical users to create and act on data insights. Together with the data dimension, the technology dimensions represent an organization’s ability to physically create and operationalize AI applications (Yams et al., 2020).

Declining costs of acquiring and storing big data on cloud services has increased organizations' desire to acquire data and capitalize on it to gain competitive advantage. Moreover, it has made it easier to track and make predictions on data in real time (Chaudhuri et al., 2011; McAfee & Brynjolfsson, 2012; Vachhrajani, 2021). Digital, AI-driven processes are more scalable in comparison to traditional processes and can easily connect with other digitized businesses. This creates powerful learning and improvement opportunities, such as the ability to produce more accurate, complex and sophisticated predictions with ecosystem partners (Iansiti & Lakhani, 2020).

Organizations can choose how to integrate AI to its technological infrastructure, by building an on-premises solution or purchasing a “as-a-service” cloud based solution from a vendor. On-premises architecture refers to software which is installed and run on computers on the premises of the organization, rather than a remote facility. A cloud based architecture has operational benefits, as providers host the software and control the services for the organization. This offers technical infrastructure on demand in the form of virtual hardware, storage and networking capability. The advantages are scalability, reliability, availability, mobility, accessibility and usability at a lower cost compared to on-premises systems. Moreover, the performance is improved continuously through user feedback. However, it is less customizable and the organization has less control over the data, which can cause data security and integrity concerns (Iansiti & Lakhani 2020; Nakkeeran et al. 2021).

To become a true AI factory, the organization must re-architect itself. It is an ongoing journey that requires moving from siloed data and experimenting with pilots to demonstrate feasibility, known as proof of concepts (Iansiti & Lakhani, 2020; Merriam-Webster, 2022). Becoming a data hub, the last stage before turning into a fully functioning AI factory, often requires further investments. It is at this stage that the organization starts to understand it will need to change some ways of working. This stage can be met with resistance, because everyone starts to understand that AI technology, rather than humans, shapes the critical path to the customer (Iansiti & Lakhani, 2020).

Iansiti and Lakhani (2020) further suggests that demonstrating the value of analytics based decision-making can be done by vendors or consultants, without large organizational and cultural shifts. The challenge is rather to accept and adopt a single source of truth for decisions on market opportunities, pricing, planning and operational optimization (Iansiti & Lakhani, 2020). However, applying deep learning algorithms does not automatically turn an organization into an AI organization. High performing AI companies are excellent at strategic data acquisition, spotting automation opportunities and centralizing data to increase the odds for drawing better insights (Ng, 2022).

3.2.2.7 Trustworthy Integrated AI

The trustworthy integrated AI component permeates the entire framework and integrates each dimension through two keywords. The keywords symbolize the backbone of taking trustworthy integrated AI into account when shaping the respective dimension. For the strategy dimension, the keywords are “ethical and legal”. For the ecosystem dimension, they are “transparency and engagement”. For the mindset dimension, they are “accountability and agency”. For the organization dimension, they are “inclusion and fairness”. For the Technologies dimension, they are “robust and explainable” and for the data dimension, they are “secure and high-quality”.

Trustworthiness of AI is important to consider, since AI systems can inherit imperfections from its developers, such as bias. Moreover, there are several risks of AI deployment connected to cybersecurity. While AI can be beneficial to increase the security of devices, systems and applications, it can be subject to attacks and be used as a tool to perform cyber-attacks (Annoni et al., 2018).

Furthermore, Heukamp (2020) argues that leaders need to be deeply concerned with ethics, trust and privacy and be able to balance the tradeoffs between the rights and need for personal privacy with the desire to provide high-quality services and profits of AI.

4. Method

The method section outlines the details of the study’s design. Firstly, it describes the literature selection, followed by study design, selection of use cases and process for data collection. Thereafter, it presents the method of data analysis underpinning the findings and, finally, addressing validity.

4.1 Literature selection / survey

The use of a systematic approach is important for literature analysis to ensure the relevance of collected material (Berndtsson et al., 2008). The research strategy for collecting relevant and recently published literature can be divided into three steps.

The first strategy included sorting relevant literature from previous university courses within digital innovation, digital infrastructure, organizing for digital transformation, governance of digital capabilities, business intelligence and data-driven organizations and leadership. It included academic papers, book chapters and online material such as video and blog articles on the topic. The next step included cherry-picking and grouping relevant articles based on reference lists.

The second strategy included searching academic papers and books through Gothenburg University library database and journal search using keywords such as “BUSINESS MODEL INNOVATION”; “AI STRATEGY”; “AI LEADERSHIP”; “AI MANAGEMENT”; “AI IN PRACTICE”; “AI ORGANIZATIONS”; “AI USE CASES”; “AI INNOVATION”; “INTEGRATED AI”;“APPLIED AI”; “AI PROOF OF CONCEPT(POC)”; “DIGITAL MATURITY MODELS”; “DIGITAL TRANSFORMATION” in different combinations.

The third, complementary strategy, included reviewing AI related government issued papers, taking online training courses, listening to podcasts, reading AI related news and white papers by AI related organizations and other non-academic sources written by well-known authors within the AI field. There is a high pace of development of AI technology and therefore important to gain an understanding of what is discussed and relevant on the market right now.

4.2 Study design

The paper was sponsored in collaboration with the national center of Sweden for Applied AI. Multiple planning meetings with the sponsor were provided to gain a better understanding of relevant discussions and obstacles that Swedish organizations related to their AI transformation are facing right now. The planning meetings provided an opportunity to identify a relevant research topic for Swedish organizations. The research design was influenced through collaboration with the sponsor. The Interview guide was largely influenced by the six dimensions in the AIMI framework (Yams et al., 2020) and an AI maturity assessment tool designed by the organization of AppliedAI (Applied AI,2022).

The paper has a qualitative research approach and is designed as a multiple case study, involving a comparison of seven implemented AI use cases. A qualitative research approach allows for a deeper and nuanced understanding of a phenomenon and underlying issues within a complex context. It is well suited for exploring behaviors, processes of interaction and experiences of individuals in real-life situations (Choy, 2014). Consequently, a qualitative approach was beneficial for this paper to dig deeper in the fundamental criteria for scaling AI and the behaviors, processes and experiences of the consultants involved. Furthermore, using a case study approach enabled a nuanced perspective of specific events (Noor, 2008).

Case studies are often used to describe a phenomenon in a field which is not yet well understood, which is suitable for applied AI initiatives. A case study enables researchers to capture ongoing processes in an organization in a fast changing context (Noor, 2008). The qualitative approach helps us gain a broader understanding of which theories can be created and tested based on further research. However, case studies can be complex because of the large volume of data collected, which creates complex interrelationships. Furthermore, the role and behavior of the researchers should be considered (Berndtsson et al., 2008).

A disadvantage of a qualitative approach is that it is a very time-consuming method of collecting, transcribing and analyzing data (Choy, 2014). The time frame of the case study was limited due to the constraints of a master thesis study. The time frame therefore affected how many objectives were possible to collect data from. With a larger sample, the generalizability could be more applicable. Furthermore, due to the lack of randomizing the sample, generalizability cannot be certain (Choy, 2014). On the other hand, this could be seen as a strength.

By addressing relevant objects and choosing a purposive sample strategy, generated a better understanding of the area, since the respondents are experts and have relevant experiences of the research area. Since the qualitative approach does not enable objectively verifiable results, the generalizability can be questioned (Choy, 2014).

Since the cases are multiple, the reliability increases, because it enables the chance of replication and therefore the findings can be considered as robust, even if generalizability can not be certain. Furthermore, because of difficulties to validate the collected data, there will be a risk that the end result becomes biased (Noor, 2008).

The planning sessions with the sponsor and the interviews were carried out during January-April 2022. The interviews were conducted in a semi-structured way, with a mix of both closed and open-ended questions. Structuring the interviews this way provided an opportunity for raising multiple issues (Choy, 2014). Choosing a slightly controlled approach when conducting the interview can reduce the risk of interviewers steering the questions towards a desired answer. This will reduce the risk of carrying a preconceived idea to the analyzing process. Additionally, it provides an opportunity to understand what assumptions exist and significant behaviors (Choy, 2014). The questions in the interview guide were grouped into categories, according to the main framework.

4.3 Selection of cases

Organization criteria: The paper selected to collect data from five consultancy firms which provide customers with AI solutions and two organizations which purchase consultancy services related to AI. All organizations are based in Sweden. A short description of each organization involved in the data collection can be found in table 2.

Case criteria : The cases were selected by the respondents under the condition that it was a completed AI use case. Preferably, the collaboration with the customer should have lasted for a longer time to enhance the chances of getting a better insight into the organization from a consultant perspective. The paper decided to investigate cases across different industries to explore if the success factors differed or were similar regardless of the industry.
The use cases selected have all been deployed in private organizations.
In Case 1, organization B is the customer of organization A.

<u>Organization A</u> Consultancy firm based in Stockholm (HQ), Sweden **Case 1**	The firm offers clients services to identify how machine learning is or could be central for their clients to operate, compete and create value. Its services range from advisory projects and feasibility studies to end-to-end development and refinement of machine learning systems and products. It delivers solutions within multiple business areas within machine learning.
<u>Organization B</u> Organization based in Stockholm (HQ), Sweden **Case 1**	A leading technical distributor of installation products, tools, machines and services for professional users in the Nordic region.
<u>Organization C</u> Consultancy firm based in Gothenburg (HQ), Sweden **Case 2**	A data science supplier which offers optimization and automatization services. It delivers customized services within AI, data science and crawling built upon text, speech, images or traditional numerical data. Has its own data science framework.
<u>Organization D</u> Consultancy firm based in Stockholm(HQ), Sweden **Case 3**	Creating AI related solutions for clients through its software platform
<u>Organization E</u> Organization based in Gothenburg (HQ), Sweden **Case 4**	A world-leading manufacturer and provider of transport solutions
<u>Organization F</u> Consultancy firm and AI product organization based in Malmö, Sweden **Case 5**	Provides consultancy services and AI products to industrial companies to improve operations by using AI and ML technology.
<u>Organization G</u> Consultancy firm based in Gothenburg (HQ), Sweden **Case 6**	Provides strategic advice and tactical decisions, development and implementation of data strategy, analytics and AI
<u>Organization H (Sponsor)</u> Swedish national center for applied artificial intelligence, based in Gothenburg (HQ), Sweden	Its mission is to accelerate the use of AI for the benefit of Swedish society, competitiveness and to improve the quality of life for people living in Sweden. It runs projects of national interest and provides infrastructure in terms of personnel, know-how, hardware and targeted training for partners and the public. It has a data factory which enables partners to make data available and access data, make use of computing power and access storage

	capacity to realize AI projects. It aims to contribute to a culture of sharing, cooperation, and action within the Swedish AI-ecosystem and to accelerate applied AI in Sweden through partner collaboration.

Table 2. Overview of each organization involved in data collection

4.4 Data collection

This part describes how the data was collected and further how it was analyzed. To identify suitable respondents, a snowball sampling method was used for finding research subjects. For this study, it meant that the researchers asked the sponsor and other connections within their social network to initiate contact between the researchers and appropriate subjects, who on behalf of the researchers asked suitable subjects to contribute to the study. The advantage of using this method was that it simplified engagement with respondents and increased the trustworthiness of the study. Additionally, it can have increased respondent's willingness and comfort to participate in the study (Balfer et al., 2012; Blackstone, 2012). The sponsor facilitated the connections through email.

The scope was discussed, adjusted and fine-tuned on a weekly basis between the researchers and occasionally with the sponsor and tutor. At first, the scope singly focused on interviewing consultants supporting clients with deployment of AI use cases, but during one of the interviews, the respondent recommended and facilitated a connection with their client, to gain insight from the customer’s perspective. The scope was therefore extended to include both interviews held with consultants and organizations which use consultants to deploy AI initiatives.

The respondents were contacted individually to set a time and date for the interview. The respondents were provided with an interview guide a few days in advance and provided with a brief introduction of the researcher's background and the purpose of the thesis. The interview guide included the main questions and a note that follow-up questions may be added during the interview. The interview guide has the same structure and questions, with some adjustments depending on if the respondent was a consultant or customer. There were two language versions of the interview guide, one in Swedish and one in English. See appendix A. The respondents are presented in table 3.

All interviews were conducted remotely via the video conferencing tool Zoom and were recorded digitally. Conducting the interview remotely allowed authors and respondents to disregard geographical distances. Criticism against virtual interviews claims that non-verbal cues, which can help to contextualize a situation, are missing. On the other hand, conducting interviews online can allow for more reflective answers and make respondents open up to ask sensitive questions (Deakin & Wakefield, 2014).

The length of the interviews were around one hour long. Swedish language was used for all interviews except for one that was conducted in English. Before the interview started, the purpose of the interview was once again informed to the respondents. The respondents were encouraged to ask for clarification if any question was challenging to understand. Before turning on the recording device, each respondent was asked to approve recording of the interview.

Additionally, the respondents were informed that only the authors would have access to the recording video and audio file and that both files would be deleted after the project was completed.

Furthermore, the respondents were informed that the answers they provided would be anonymized in the study. In the result section, each respondent has been assigned a number. However, there is a risk that involved parties can identify their own contribution and other organizations in the study, based on the description of a use case, product and service offering or a direct quote (Walsham, 2006).

Respondent	Organization	Role	Process	Date	Language
Respondent 1 Case 1	Organization A	*Consultant*	Semi-structured interview, digital.	16/03/22	Swedish
Respondent 2 Case 1	Organization B	*Head of labs and applied AI*	Semi-structured interview, digital.	20/04/22	Swedish
Respondent 3 Case 2	Organization C	*Consultant*	Semi-structured interview, digital.	23/03/22	Swedish
Respondent 4 Case 3	Organization D	*Consultant*	Semi-structured interview, digital.	25/04/22	Swedish
Respondent 5 Case 4	Organization E	*Product Owner*	Semi-structured interview, digital.	07/04/22	English
Respondent 6 Case 5	Organization F	*Consultant*	Semi-structured interview, digital.	08/04/22	Swedish
Respondent 7 Case 6	Organization G	*Consultant*	Semi-structured interview, digital.	20/4/22	Swedish

Table 3. Display of interviews.

4.4.1 Data Analysis

The data was analyzed using the theoretical lens provided by the conceptual framework. The aim of this method is to identify themes and patterns in the data which can be related to the research question.

A combination of inductive and deductive approaches was chosen for the paper. An inductive approach is driven by empirical data, while the deductive approach is theory-based (Cooper et al., 2012). In the early phases of data analysis, an inductive approach was used to understand the data set on a deeper level, while the final phase had a more deductive approach to connect the data to the theory and theoretical framework.

After transcribing all the data, the content was read through multiple times to gain an overview of the collected data. To gain the most accurate and unaffected result as possible, the recordings were listened to several times when ambiguities emerged. We started by coding and clustering sentences to form potential quotes based on the AIMI framework and its seven dimensions. Thereafter, we coded additional information that was of relevance based on the collected data to identify other considerable success factors for further scaling of AI, which were not accommodated within the framework.

To be able to compare the different use cases and gain a more nuanced discussion around the research question each case was categorized at a maturity stage. The maturity degree for each use case is based on the framework's maturity scale from Foundational to Integrated. Data was coded and clustered based on how the framework defines and categorizes the different maturity stages. This was done to gain a starting point for each case and further to identify if there were different dimensions which were more crucial than others, based on which stage of maturity the organization is located/stationed on its journey towards integrated AI.

4.4.2 Validity

Validity describes the relationship between what the paper intends to examine and what is actually examined. To ensure trustworthiness, it is important to address the process and outcome of the analysis. Firstly, by emphasizing strategy (what was planned) and the process of data collection and analysis (how the study was made). Secondly, by acknowledging the sources of how the analysis is based and to consider to what extent the sources are appropriate and relevant as a basis of the study (Berndtsson et al., 2008).

The paper chose to interview representatives from consultancy firms about use cases they have been involved with for their customers' AI deployment, instead of interviewing the customer’s stakeholders. This naturally brings benefits and disadvantages to the validity of the study. A benefit for conducting the study this way, is that the consultancy firm can provide an objective view of their customer’s maturity when it comes to AI, because of their relevance, expert competence and experience within the research area.

However, a disadvantage for conducting the study this way could be that the consultancy firms overemphasize their contribution to realizing the AI deployment and because of their varied access to the full extent of their customer’s organization. The use cases can lack the depth it would have had if the customer’s stakeholders had been able to contribute with their perspective. One of the use cases includes both the perspective from the consultancy firm and a customer stakeholder.

The paper further reflects on the choice of respondents and cases and acknowledges that there may be a weakness in gaining access to the respondents through connection via the sponsor of the study and that the respondents may have selected suitable use cases based on the interview guide sent in advance, rather than choosing a random. However, the choice of method was beneficial to gain the necessary data collection within the time limit for the study.

In qualitative research, the researcher takes an insider perspective and becomes a part of the problem situation. Problems are analyzed by investigating and interpreting human and organizational aspects in relation to technology. As humans and organizational conditions change over time, the pre-condition for the study and the analysis of the problem change. Furthermore, it is important to acknowledge one's own initial understandings of the phenomena being analyzed and one's own behavior during the research process (Berndtsson et al., 2008).

Despite the small risk, the study further acknowledges the existence of bias from the researchers' own preconceptions on the research area and that the result from the study can influence the organizations involved in the study. However, because the researchers had limited awareness of the AI phenomena and the cases were completed at the point of data collection, there is little risk that changes and circumstances which change during the project or bias can have affected the result. Moreover, the paper has a bias towards private organizations, rather than public organizations.

5. Results

The result section presents the findings of the study. Firstly, Table 4 illustrates the summary and aim of each use case to provide an overview and context for each use case, which the findings are based on. Thereafter, the findings are presented and structured after the six dimensions of the theoretical framework (the AIMI framework). The dimensions are Data, strategy, ecosystems, mindsets, organization, technologies and the framework's core component, trustworthy integrated AI. Lastly, an additional theme is presented, which was identified during the coding of the collected data, this component is called "Metrics for scaling".

5.1 Use cases

The respondents were asked to choose a use case based on the criteria that are described in the method section. Table 4 provides an overview of all use cases involved in the study, including industry belonging, a short summary of the implemented AI solution and the primary objectives of the implementation.

Use Case	Summary	Aim
Case 1 Industry: Retail	Developing a recommender system for website and app	Increase sales and customer satisfaction
Case 2 Industry: Pharma	Partly automatic trading of generic medicines	Replacing manual analytics tasks

Case 3 Industry: Infrastructure	Identifying errors in infrastructural designs	Replacing parts of the manual quality control process
Case 4 Industry: Heavy machinery	Predictive Maintenance of vehicles	Estimating time-to-failure for a product to enhance service offering
Case 5 Industry: Manufacturing	Using data analysis on manufacturing process	Improving product quality
Case 6 Industry: Financial services	Resource planning	Predicting staffing needs and removing manual planning tasks

Table 4. Use cases

5.2 AIMI elements

5.2.1 Data

That data is a central prerequisite for AI is a consensus shared among all the respondents in the case study. Respondents 1, 4 and 5 especially highlight that data generates value and found it helpful that their customers already understood that data can be collected from internal business processes or external data sources. A recurring problem raised by multiple respondents was the amount of available data to feed the AI solution with. For use case 6, there was a sufficient amount available to scale, because it was possible to reduce the scope to a level where the amount of data available was sufficient for the purpose it intended to solve. For limited scaling, a small amount may be sufficient, but in order to continue scaling for an expanded scope, data quantity is particularly important, which is emphasized by Respondent 4.

Moreover, data quality is mentioned as an important factor for scaling by multiple respondents. For example, annotated, i.e. labeled data, was especially important for scaling use case 3, because it helped to clean, format and classify the data, according to Respondent 4. For further scaling, Respondent 7 emphasizes that certain data can and cannot be reused for other purposes, which is important to keep in mind. Furthermore, data variation mentioned by Respondent 6 as well as access to the right type of data suggested by Respondent 5, were reasons why the team managed to scale. For further scaling, Respondent 5 mentions data management and a data related infrastructure as important factors.

We met a number of different technical challenges during the implementation, since the data was limited. Admittedly, there was much accessible data, but it was exactly the same which gave no variation, which did not provide any new information to the solution (Respondent 6)

Data quantity and quality are crucial…we met some issues because other entities in the group wanted to have the same solution… But that means we need to build a model based on their data. We could not reuse the data in this case (Respondent 7)

*There is almost always too little data, given the specific things we want to solve…at an early stage they understood that they would need to annotate (label) their own data to solve the issue. Those organizations who understand that immediately and think that it is worth it, they almost always succeed (*Respondent 4)

It starts with the data, because at the end of the day you can only do so much with the data that you have. If you don't have the right data then we cannot build models, build predictions or make services…then you have to go deeper and look into the infrastructure and how this data is being managed and how you're able to actually work with it (Respondent 5)

There are two philosophies for how to look at the value of data in the AI community, according to Respondent 6. One philosophy believes that value lies within the data itself. While the other philosophy believes that value emerges when it is interpreted by experts. By gaining insight into the processes which generate the data from the people who work with the processes. Respondent 2 mentions that it is a question of maturity in identifying data points and data sources where value can be extracted from data created together with the customer. Furthermore, Respondent 2 suggests that when becoming a more data-driven organization, external data sources can be just as valuable as internal sources for the business.

We have a maturity journey to do in looking at other data points and consider them as such, and using external data sources to inform us and make better decisions. Here we have a long journey to go, so we are not very data sophisticated or data-driven today, but we need to take that path (Respondent 2)

I think we definitely value data and the group has been investing in logging this data and seeing the importance and understanding that the world is moving towards a more data driven approach. And I think we are one of the first use cases of leveraging this data. The support that we receive from the executive management, we experience that since they have made this investment…a data mindset is very important, you have to have a certain mindset in the organization about how to handle and structure data and how to organize the governance around data and so on (Respondent 5)

5.2.2 Strategy

In the majority of the interviews, the respondents emphasized the importance of the use cases being linked to the overall business and that it fulfills a business value. That business value is important for scaling is a common statement among several respondents. Respondents 3 and 1 express this clearly and refer to fulfillment of a business problem as the most important factor for successfully scaling AI. Respondent 2 points out four criteria for the choice of use case where customer value was the most important, followed by business value, technical complexity and organizational feasibility. Respondent 5 particularly emphasizes how the business model has changed with AI, as the organization has been able to offer a new type of AI integrated service offering. Furthermore, Respondent 5 suggests that the scaling was successful because of the opportunity to both use big data to find patterns while innovating the service offering in a cost-effective way

That is really the only reason for investing in AI, it is that you should gain better insights to enable better business decisions…There are so many image recognition projects in AI, but they do not solve a problem. For a poc / pilot to survive, it must solve a business problem (Respondent 3)

the customer value weighted most, thereafter the business value and then technical complexity and organizational feasibility (Respondent 2)

Predictive maintenance service is tied to the service contract, which is basically a subscription or an insurance for the customer ...This new way of monitoring the vehicle and the different components using AI and big data. We see that it's a way to reduce cost… this approach of using big data, we don't necessarily need all this information, you can find patterns in other ways (Respondent 5)

Multiple respondents raised the importance of AI in proportion to the overall business mission and digitalization strategy. Having a specific AI strategy seems to be a rare phenomenon among the organizations. In use case 6, the customer has a written AI strategy, however the respondent clarifies that the strategy was written in a manner that is unrealistic for a practical purpose. None of the remaining use cases had an AI strategy, but refer to overall business and/or digitalization strategy. Respondent 1 claims that having an AI strategy does not need to be a success factor, the importance is having AI as an available tool in their toolbox. Furthermore, case 1 raises the importance of balancing efficiency and innovation efforts, where AI can be used as one of several means to improve operations and business development.

AI can be used in multiple ways, both for increased customer experience and efficiency. We choose to let our business goals and strategy guide us and to use AI as a means to fulfilling them… the concrete choices of which tools to choose from must be made based on the scope. The most effective way to do this is to gain an overview of which current use cases are aligned with our overall digitalization strategy (Respondent 2)

It's not sure that organizations need to have an AI strategy to succeed, what they need to understand is that AI is one of many tools in the toolbox (Respondent 1)

No, there was no clear AI strategy. There was only an intention to test the technology, and I believe the customer was surprised over how well the AI solution solved their problem (Respondent 6)

They have a strategy, but it is fuzzy and not suitable for practical implementation in an optimal way. I think it is important to have a strategy to be able to scale AI, but I think that strategies tend to be something which companies use to be able to say that they have one, rather than something which works in practice (Respondent 7)

it is something that has been brought forward in the business strategy and the whole Group strategy (Respondent 5)

Although there were no clear indications that a specific AI strategy was important for scaling, the respondents still suggest that the goal of using AI for business purposes was important.

The fact that there is a clear ownership in the organization, with an involved management team which has a central decision to drive AI development from a strategic perspective to develop the organization, is emphasized as an important factor by the majority of respondents. Additionally, allocation of sufficient resources to experiment with AI on a smaller scale is further considered crucial. Respondent 2 mentions portfolio thinking, where the customer sees not just one but several potential AI use cases among other potential investment areas. They are comparing risks to rewards, in order to be able to handle expectations of what AI can achieve.

*Since last year, a much stronger focus has been brought to AI (*Respondent 5)

We are rolling out a more agile way of working when it comes to digital development, with an active ownership of the own digital roadmap (Respondent 2)

There is a sponsor which has been involved from the start and which we have discussed the scope with… it would not have been possible to scale if there was not already a central decision to invest in AI (Respondent 4)

we are building our investment portfolio based on risk / reward… we work actively with it and try to quantify the risks and rewards as clearly as possible (Respondent 2)

when the customer started, they had a clear goal and vision, which is the most important…. and there are several other initiatives in the pipeline, they do not consider them as individual investments (Respondent 1)

When it comes to the choice of buying already developed AI solutions from vendors or to recruit and build in-house competences, the respondents' answers are contradicting. On one hand, there are benefits of buying standardized AI solutions, since it does not require large-scale investments. On the other hand, several respondents suggest that there is a strategic value in understanding the components of the AI solution and therefore develop in-house AI capability to ensure long term competitive advantage. The respondents suggest that ideas for new AI use cases usually arise from identified efficiency needs in-house processes. However, the respondents also hint of external influence, in the form of competition by new entrants and customer demand.

Our strategy was to seek support from consultants to start building a first AI use case, so that there was something for our future employees to work with and then be able to proceed with internal resources (Respondent 2)

it is an organization that wants to profile itself with AI solutions“ (Respondent 7)

Almost all existing players on the market have allied themselves with other large partners, and our customers were not eager to use any start up and just buy a “Black box” AI solution. They felt that this was so core to them that they wanted to build it themselves, so they could own the content of the black box” (Respondent 4)

5.2.3 Ecosystems

Few respondents mentioned the ecosystem aspect as an important factor for scaling AI. Respondent 5 highlights this dimension as an important aspect and something the organization is actively working with in related fields, linked to collaboration in the organization's digitalization journey or specific technology development. However, the collaborations when it comes to AI use cases are somewhat scattered. Respondent 1 further mentions the importance of the mutual value you need to contribute to your ecosystem. Respondent 3 mentions trust between parties as an important factor when scaling AI. Collaborating with external parties can be beneficial, but as the respondent points out, customers are worried about how collaboration of AI development can affect their business.

We strongly believe in being a part of an ecosystem… you have to be a part of the ecosystem to be a part of the development… we must both be able to extract value from the ecosystem and contribute with value back to it (Respondent 2)

We are definitely investigating external partnerships… Partnerships are encouraged at a large scale in the organization, especially for the development of new technologies…within AI there are partnerships with certain companies, but it is somewhat scattered (Respondent 5)

Many of our customers are actually anxious to involve and trust other parties to collaborate on such vital business areas. If an organization decides to rely its future on an external party, then they really have to leave their comfort zone. And that, in fact, can take time. Ideally, they would prefer to do it internally, but they cannot do it themselves (Respondent 3)

5.2.4 Mindsets

Multiple respondents suggest that a potential success factor may have been that the organization has had a permissive organizational culture which encourages experimentation with new technologies and a mindset of considering AI investment as a learning process. There is an understanding that the investments they make now can pay off in the long run, by reusing parts of what has been created and learned in future use cases. For example, Respondent 2 mentioned that their customer had an openness and an intent within the organization, to gather lessons learned during the scaling and a sense of humility towards not knowing everything. Respondent 5 further emphasized that the team took into account that the AI initiative required change management measures to sell the concept internally to "get everyone onboard". Additionally, Respondent 5 mentions that there is a common understanding that everyone in the organization can contribute ideas and an openness to ideas coming from different parts of the organization. The right mindset was absolutely crucial, according to Respondent 2 as well as aligning operations accordingly.

Some organizations overcomplicate things by making declarations of intent and reporting what to do, but forget they need to start taking action. Even if you are a large organization and have big ideas of what to do, you have to start small and start experimenting (Respondent 3)

There was an intent from the client to make sure to realize an effect. And that they had to work with the infrastructure, data, ability that they had and make the most of it and to improve over time ... Mindset is the most crucial for AI scaling … to have a clear goal and level of ambition, as well as the organization's ability to align and focus on realizing their goals… we discussed lessons learned very openly… So there was a humility for what they can do and that this is something they need to learn step by step (Respondent 1)

It required change management everywhere from the tools that we're using, moving to the cloud, how to evaluate performance…Of course, not everybody can be involved, as people are focused on other things. But we definitely see a need of ideas coming up from very different parts of the organization (Respondent 5)

Multiple respondents agree that focus is important for scaling AI. Respondent 3 highlights the importance of clarifying the focus and starting with one task at a time. Respondent 2 further suggests that it may have something to do with the existence of a start-up culture. Respondent 4 compares the culture of an organization that works with R&D or product development, where there is an understanding and acceptance that certain investments will not succeed or the mindset of a start-up which can focus on perfecting one specific feature, product or service.

It is about shaping a start-up culture in a large organization… I have been involved in scaling many AI use cases, and it is partly linked to this specific case, but if I were to take another use case, it is pretty much the same, it's not a huge difference. What separates (incumbents) from digitally born companies and drone startups is that they have a much better focus (Respondent 1)

Organizations that are used to R&D processes and product development seems to have a little easier to scale AI, because they know that everything they invest in will not turn to gold… they might invest in 5 different ideas and only 2 of them are realized (Respondent 4)

When it comes to how the management team considers AI, support and involvement in the AI use case, some respondents are divided. While Respondent 5 believes that management's involvement had positive effects on scaling, Respondent 7 suggests that their involvement made it more challenging, as the management had expectations that did not correspond with reality. Other respondents suggest that the support and involvement from management was not more than allocating resources or follow-up of certain KPIs, such as for Respondent 3.

The management team has absolutely influenced the use case, and it may have partly made it more complicated, because they wanted to make it more advanced than it needs to be… they requested aspects that are not needed, but in their world it provides them with something cooler to talk about… they have very high expectations of that AI can do and expect it to be possible a little too easily (Respondent 7)

Executive management is clearly pushing for what we're developing. Of course, they're not involved in the day-to-day work, but they're very eager, and we receive much support from them. Especially if we need to escalate a certain issue we have (Respondent 5)

The management team were not really involved at all, except that they gave their approval for it (Respondent 3)

Multiple respondents suggest that a driven leader, together with a strong team, creates a favorable environment for scaling AI. Respondent 5 especially expresses a strong commitment, enthusiasm, excitement and pride, as well as the importance of coherence to build a team spirit to deliver. Respondent 4 further suggests that onboarding of newly hired expert competencies can create a sense of confidence and belonging.

*There has been much development ongoing for a long time, and we are at the tipping point where everything is coming together. It is somewhat stressful on one hand, because there are still several unknowns, but also very exciting because we're about to see the rewards for all these efforts. I'm super proud of the team. I think we're building the coherence and the team spirit here to actually deliver (*Respondent 5)

We had great support from the project manager who really wanted to achieve the scaling (Respondent 4)

The first quarter of the year we had help from consultants and then our first own employees joined. They were actively involved in the project initially, as an onboarding to get acquainted with what was built and thereafter involved in building it themselves (Respondent 2)

5.2.5 Organization

A potential success factor may be that there was a clarified ownership of the AI use case and a smaller, dedicated team taking care of the AI questions. As well as setting expectations for what is to be achieved. Respondent 3 mentions the importance of placing ownership correctly in the organization in order to reach its full potential.

It is important that the business is involved in decision-making about AI, not just the IT department, according to Respondent 3. To facilitate coordination and reporting, it can further be beneficial to work in smaller teams. As further presented in Respondent 6's use case the organization created a small AI group that works together with the organization's process improvements and quality work.

Furthermore, it has been important to involve relevant stakeholders who hold knowledge of current processes and whose work situation is affected by the AI deployment, so that these people can be involved in designing how the new solution will look like, according to Respondents 4, 6 and 7. According to respondent 7 strong communication has been important to come to the right solution for the specific use case and map the risks and opportunities with AI overall. Respondent 5 further points out the potential breadth of collaboration between fields in the organization using AI, breaking silo thinking and encouraging cross-divisional collaboration.

The customer has an innovation board which we discuss and map out problems areas within the organization and identify potential risks and opportunities using AI. the innovation board that has owned this project from the beginning… the person who has done the actual planning has also become an important stakeholder. Because he/she is the one with the knowledge of how this solution should work (Respondent 7)

The sponsor had the role of allocating resources and the overall intention. He/she then withdrew and delegated the use case to the person who works in the process. There was also a project manager who became involved. So we had both a process expert and a project manager on their end (Respondent 6)

The IT department is just one part of the organization that scaling an AI solution depends on. Yes, they have to open APIs, and we have to gather data and thus IT is involved. But we are not dependent on the IT department in that way. The IT department is not sitting on the *business problem. Many companies that want to invest in AI make the mistake of believing that AI is an IT project. That is not the case, because IT plays a different role. The IT department is a gatekeeper for new things and should make sure that all systems works as intended (Respondent 3)*

Both the small AI team and the process quality department together solve this use case (Respondent 4)

We're involved in many projects all over the world, collaborating with multiple engineering and business teams within the group… Finance is also super interested in what we're building (Respondent 5)

A factor that seems to have had a positive impact on the upscaling of AI is the ambition that the organization will be able to take over the AI solution after a certain period of time. However, this has not occurred in the majority of the use cases. Respondent 3 suggests that the rapid development in AI makes it difficult to transfer skills between consultant and organization, which creates a mutual dependence. Which strengthens the importance of a healthy relationship between the organization and its AI supplier. Building internal competence tends to be a challenge for most organizations, and the partnership with consulting firms has been an opportunity to gain access to expert competence needed to scale their first use case. For most organizations, this has meant continued scaling of the same solution and additional use cases. Moreover, there is an understanding that the organization needs to recruit, train, retrain and actively work to retain expert competence, suggested by Respondent 5.

We often write agreements with customers that they should be able to take over what we have developed in 2 years' time, but we have customers that we have worked with for over 8 years that choose not to do so (Respondent 3)

They have the business knowledge, they might have the data knowledge, but then, they have no more. AI knowledge is generally very difficult for companies to build. These are not programmers, they are AI artists who want to work with other AI artists. If the newly hired person is not challenged and keeps having to do boring A / B testing, that person will quit after 3 months. Therefore, it is very difficult for companies to build such competence in-house (Respondent 3)

It has been a large competence ramp up for the past year, hiring many new people, bringing in many consultants as a way to scale up quite quickly…and much training to build in house competence, development to know more about how to handle large datasets, how to write a better, more efficient code and how to develop models (Respondent 5)

However, expert competencies are not all that is required. Several respondents mention the importance of having a basic understanding of AI to scale the use case. A basic understanding is further important when it comes to contributing with ideas, understanding organizational preconditions, managing existing AI solutions and troubleshooting, in case the AI model starts to behave incorrectly. Respondent 3 points out that a business understanding is just as important as understanding AI. Additionally, Respondent 5 highlights the importance of different competencies coming together, where each competence area needs to communicate and align with others to realize the intended effect of the AI solution. Several respondents further emphasize the importance of having basic in-house competences, for the purpose of setting the right requirements towards suppliers.

Application developers are needed to be able to build the platform around the AI solution, but also general AI knowledge. It is not very critical in the actual takeover of the AI model, but if the model would start behaving strangely, they do not have the competence to troubleshoot why (Respondent 7)

There is no structured way for employees to come up with such ideas. I would say that a basic competence is very important because it creates the conditions for coming up with ideas. Even though there is a group that works with innovation in AI, there is a lack of basic competence throughout the organization. if there would be a basic AI competence, there is automatically a much larger number of people who can come up with ideas and suggestions to streamline. I am convinced that it already exists in many places in the organization, but we do not have insight into all parts ... it will also be easier to motivate employees to why there will be an AI solution that they will use. It will also be easier to accept it if the employees has a certain degree of understanding what it actually means (Respondent 7)

We have about 20 people involved in the solution. I would say that it's almost an even split between IT and engineers. On the IT side, it is a mix of consultants and employees… for example, some are working on taking the data that we produce and the predictions and thereafter display them into front end widget visual support. The service that is actually used by the customer operation. We need to provide them with intelligence in a visual format. Then we have an analytical pillar, which are experts both in making models and handling data at scale, which can communicate with the rest of the engineering teams. We also have a service pillar which interacts with our brands just to make sure that the intelligence that we're building is actually going to be useful for them. But also to expand on what we're doing already to explore new opportunities (Respondent 5)

We will conduct the training iteratively. We start on a small scale with a lecture format to calibrate that it works for our recipients in the business… with the goal to provide our employees with the essentials, so that they themselves can become better requesters in the future. There is where we see a large gap (Respondent 2)

It is about them becoming better at collecting data. They must have certain internal skills, and they choose the level of how much you should know about AI. If you want to be a good requestor or if you want to develop your own solution or if you want to become an AI organization. In this case, it is natural that they will end up being a good requestor, i.e. they have some internal competencies to be able to evaluate suppliers and write relevant requests to have effective projects with AI suppliers (Respondent 6).

Another potential success factor for scaling AI solutions seems to be small scale organizational changes. The impact on daily operations tends to have been small, such as streamlining certain processes and removing monotonous tasks. Respondents 1, 2 and 3 advocates starting on a small scale and gradually expanding by making iterative changes. It is about expectations management. Be able to identify people in the organization who are receptive to a changed way of working and then engage and activate these people who can lead and promote the use case to get more people onboard.

If you are to succeed, you must choose AI projects that give as little impact as possible. Projects that bring a large impact to existing procedures, business models or other ways of working meet resistance. Therefore, you should not start there. You should start with things like removing manual steps for an analyst. The analyst does not need to change his/her way of working, it only becomes more efficient, which is what we have done for this medicine organization (Respondent 3)

This was a rather low-hanging fruit that did not require a huge organizational change (Respondent 7)

Do not start immediately with the difficult algorithm. Instead, start talking about things that people can understand and reason around… There was a clear sponsor and product owner…. When it comes to expectations management, gaining access to data, understanding business requirements and activating people, the product owner was very involved and that was a decisive factor for the implementation. It is important to understand which people in the organization are receptive to a changed way of working (Respondent 1)

P*eople working in very different ways and storing information in different places create frictions for enabling faster development of AI* (Respondent 5)

5.2.6 Technologies

To scale AI there may be necessary to invest in some infrastructure. Some use cases have chosen to scale AI with an own on-premises solution, while others have chosen cloud solutions. There is a benefit of scaling AI within a cloud solution, as plenty of the respondents suggest. However, some organizations prefer on-premises solutions to ensure access and protect sensitive data.

We are doing large investments in systems aligned with our digitalization agenda. We buy already completed systems, but at the same time we are making investments in our own infrastructure to take control over our data flows and the customer's experience (Respondent 2)

Moreover, there is an ownership question related to the technology that enables AI. There is a certain degree of convenience of using consultancy firms' infrastructure and development of application services that are sold as “as-a-service” subscriptions to the customer. Another layer of this dilemma has been to build AI solutions in large tech companies cloud environments, such as Microsoft Azure or Amazon Web Services. The cloud solution is more cost-efficient than on-premises solutions, in regard to hardware investments, development and recruitment of in-house ability for managing maintenance, according to several respondents. Additionally, a cloud solution makes it easier to regularly update the AI solution’s code. However, the cloud option suggests that the organization can take full control over their AI solution and the infrastructure. Further, they don't have the flexibility to fine tune the AI solution and make it fully customized with current processes.

We often build our own solution, put it on the cloud, open up our API and then inform the customer how their system should interact with our API… Sometimes we make on-premises solutions where our algorithm is in the customer's server halls, which means we have to store our code with them. There is no problem with that, but it becomes a little harder to update the code, for example (Respondent 3)

The customer helps to some extent with infrastructure such as servers, but the development itself is entirely us. We also continue to be product owners, because the customer do not have the knowledge internally to take over such a system (Respondent 7)

In this case, the customer chose to make an on-premises solution, which is run by themselves in their network… the customer generally does not have an infrastructure today that allows AI scaling (Respondent 6)

We're making a movement to the cloud, so we're shifting away from all the on-premises data science solutions that we see are not really scalable. They're very expensive to maintain and require much expertise to develop (Respondent 5)

AI technology is changing at a rapid pace which may imply that even if the organization is making major investments in infrastructure this could be outdated fast and instead create legacy. There is a technical burden of scaling AI with on-premises solutions. Respondent 5 suggests this could entail silo thinking and add complexity when scaling. On-premises solutions require larger infrastructure investments and have negative effects on coordination and decision-making cross-functional in the organization. Moving towards cloud solutions will lessen the burden of the organization's infrastructure legacy and decrease the risk of even more legacy.

If the organization is not a digitally born tech organization, it usually does not have systems built in a superior way and they are not connected in a good way either (Respondent 7)

Perhaps the key enabler for us to go further is to narrow this chain down to make it simpler by using new technologies that don't require all the legacy system and all the legacy architecture that we have built…The challenge here would be to try and narrow or to lessen the burden of the organizational structure behind it (Respondent 5)

It's a technological burden because these infrastructures are not flexible at all. They have not progressed in time with new technologies as fast as a provider like Microsoft or Amazon Web services where you're pretty much can assure that you're going to have the latest functionality (Respondent 5)

Respondent 5 briefly suggests that the organization has a central platform for storing AI information and states that having this platform makes flexible design possible, which enables it to offer custom made solutions and reuse AI infrastructure in other use cases. However, Respondent 7 establishes that not all infrastructure can be reused.

In true Swedish fashion we have thought of this central platform to be like an IKEA warehouse. A place where you can have different items that you can choose from. Basically, either you have the full solution, i.e. a full bedroom with everything included or you can buy the individual tables and beds to make it your own. Therefore, we are building a platform that *enables different stakeholders to have flexibility of designing custom tools for certain markets (*Respondent 5)

*Everything is custom-made for this initiative and not much is reusable (*Respondent 7)

5.2.7 Trustworthy Integrated AI

Respondents 2, 3 and 7 emphasize that ethics, data quality and bias are important aspects to consider when scaling AI and to make sure that these aspects are handled appropriately. Respondent 2 even has a special process for it. However, in the available use cases, it has not been necessary to take highly sensitive data into consideration, in regard to personal identification. Respondent 7 emphasizes that ensuring cybersecurity has been important in scaling. One way to succeed was to deploy the production environment into smaller prototypes, which were approved over time.

We ask that question in every case we work with. Do we have any ethical aspects to take into account? For the medicine organization we did not really have that… in other cases where we analyzed criminal convictions, the data was very sensitive when it comes to data privacy and security aspects and required another level of difficulty, but you should not be afraid of ethical aspects or GDPR (Respondent 3)

We have a checklist that we usually go through (Respondent 1)

we have had many discussions with the customer’s IT and security departments…In order for us to receive a “go” on deployment in production, we had to reframe the scope into different parts, we did not need a go on the entire production environment at once, a go on the first prototype was enough (Respondent 4).

5.2.8 Metrics for scaling

The Respondents' responses were diverse when it comes to using specific metrics or criteria to go from a POC to scaling AI. What everyone pointed out was the importance of quickly proving a business value to management and adapting to metrics that were important for the business, proving that the AI solution works better than the current process, balancing a low risk with a high reward.

Our contact person sourced funding from management to conduct an AI project. After the project was completed, the team could prove to management that it succeeded by generating a return on investment, and the management team gave a go to invest in further projects (Respondent 3)

The most important thing to move forward was simply the powerful solution we were able to offer them. This is one of their most important products and the AI solution increased the quality by 20% (Respondent 6)

It was simple to make something that provided value at once… it was quite simple data to process, so we could build the model quickly and make a platform for it, which provided a large impact at a low cost (Respondent 7)

Something that was clear from the respondents' answers was to scale the use case in several steps. One respondent mentioned that they built a minimum viable product (MVP), but that it is important to take into account user requirements in order to find a balance between basic functionality and user-friendliness. Moreover, there is a point in involving experts which can validate the solution and support the deployment to evaluate what is more and less important. For example, Respondent 4 mentions that it was more important for the organization that the AI solution provided more "false positives", because the AI solution was validated by a human. Furthermore, there was a requirement for a certain user-friendliness, to be able to have something more than just an MVP to evaluate how the solution can integrate with current processes.

A quality reviewer had to test to check and determine if the results were good enough ...The first scope was far too minimalistic to be used, and there has been much discussion about what it takes for that to be useful. We can ignore the fine-tuning, but some basic functionality must be there because otherwise they can not evaluate the result…The requirement was set that there must be enough user-friendliness to be able to evaluate whether it works in the current process. Everything beyond that will be a version 2 (Respondent 4)

We set our own criteria about model accuracy, precision, recall about all these sorts of metrics that enable us to assess model performance…this way of working is quite new in the group, there is no real strong focus from the brands from the commercial organizations to assess the model…. It's more that they're asking us to develop a model to monitor particular components, and we tell them OK, we're ready with the model. It's on our own initiative that we decide that. The true test starts when we scale in production. Because then, the brands will compare the cost increase of the service contract (Respondent 5)

There were two criteria that were crucial to move forward. One was quality of the AI model, the other was to succeed in building an interface that can plug into the current quality process (Respondent 4)

6. Discussion

In the discussion section, the paper first classifies the organizations based on the findings in the results section. Thereafter, the different dimensions of the AIMI framework are highlighted to clarify what organizations need to scale AI. The discussion first discusses the limitations of maturity models, followed by an identification of which dimensions should be prioritized in order to scale a first use case and make AI valuable. Lastly, it continues to identify what is required to reach a higher level of maturity towards AI integration for business model innovation.

6.1 Classification of AI Maturity

The organizations involved in the paper were each allocated to a maturity stage, based on the results from the use cases. This classification is illustrated in Table 5.

Maturity stage / Use case	Foundational	Experimenting	Operational	Inquiring	Integrated
1			X		
2	X				
3		X			
4				X	
5	X				
6		X			

Table 5. Classification of Cases Overview matrix

Comments on classification:

1. The index indicates that the organization is moving from a more operational to an inquiring AI maturity stage. It has an understanding of the transformational power of AI and is working on a strategic and organizational alignment and governance of AI capabilities. It is for example making efforts to recruit the necessary competences and build internal coherence around AI initiatives, driven by a small central unit, which suggest an inquiring maturity stage. However, it has yet to develop its own external ecosystem with academic partners and/or other companies, as well as diverse types of specific/open-ended collaborations, with exception for the consulting firm.

2. The index indicates that the organization is moving from a more foundational to a more experimenting stage. There is a curiosity about AI and grassroot efforts, but the organization still has a limited understanding of it and its applicability to the business. The focus of the use case was to make internal processes more efficient, focusing on short term ROI. There is no own data infrastructure involved, as the AI solution is provided as “as-a-service” or any particular data-driven experimentation culture and little management involvement.

3. The index indicates that the organization is moving from an experimenting stage to a more operational stage. There is less hype around AI and the organization is beginning to change its mindset about AI's impact, as a consequence of market competitiveness. It is developing an understanding of the iterative, experimental process needed for developing AI and is moving from a limited understanding and competence level to build its first relevant AI application.

   The organization has a central decision to invest in AI. It has a small, dedicated AI team and has made initial infrastructural investments to own the content of the AI solution. The organization is experimenting with AI, but still has a limited data infrastructure and a data driven experimentation culture. It has some data pipelines in the form of labeled data. However, the focus of AI applications still lies on "bolt-on" AI applications to plug into internal processes for efficiency gains.

4. The index indicates that the organization is moving from an inquiring to an integrated stage. The business understands the transformational power of AI for the organization, market and industry and develops the necessary strategic orientation, infrastructural investments and mindset to achieve it. It has a centralized platform for data management and an innovation-based product and business strategy exploration which is gaining momentum, as the use of AI has been fully integrated within its service offering.

   While the organization is external and future-facing in regard to its ecosystem and R & D and has an extensive external ecosystem with academic partners and other companies in AI related areas, it has yet to develop its own external network for AI specific purposes or encouraging diverse types of collaborations. Furthermore, although it still has a relatively small, dedicated team working with applied AI, it remains unclear how wide the strategic orientation stretches over the whole group.

5. The index indicates that the organization is moving from a more foundational to a more experimenting stage. While it has a small dedicated AI team working in collaboration with quality assurance teams to improve product quality via more efficient internal processes, the level of internal AI competences is still low. Even if the organization is building an on-premises solution, the data pipeline is still limited without much data variation. There is no AI strategy, but an intention to test the technology. The focus remains on "bolt-on" AI applications for improved product quality through more efficient processes.

6. The index indicates that the organization is moving from an experimenting stage to a more operational stage. While there is still a certain hype around what AI can and cannot do for the organization, it has a mindset to profile itself with AI and keep scaling the first use cases on multiple geographical locations within the group. It is developing an understanding of the iterative, experimental process needed for developing AI and is moving from a limited understanding and competence level to build its first relevant AI application.

   The organization has a small, dedicated innovation team that handles AI ideas and has made initial infrastructural investments to own the content of the AI solution. The organization is experimenting with AI, but still has a limited data infrastructure or a data driven experimentation culture. The current focus of AI applications still lies on “bolt-on” AI applications to plug into internal processes for efficiency gains, rather than looking for innovation opportunities.

Based on the paper’s classification of each organization, the findings suggest that most cases had a lower degree of maturity, while use case 4 indicated a higher degree. This was reflected in how the respondent approached the interview guide. The organization highlighted more innovation-focused aspects to a greater extent and related to cause and consequences of its underpinning maturity in a short and longer term perspective. e.g. how to look at the ecosystem's impact on AI integration. While Respondent 5 highlighted dependencies with a greater capability to influence, other respondents indicated that organizations need to reach an overall higher maturity, before influencing other parties and taking an active role in the ecosystem for common AI development orchestration.

In line with the dimensions of the AIMI framework, the findings suggest that scaling AI requires a combination of multiple factors, more or less dependent on each other.
All aspects of the framework were important, but which dimensions that were the most vital for each use case varied and could be distinguished by a shorter or longer-term perspective.

6.2 Limitations of maturity models

It was challenging to classify the different organizations into one stage of maturity. For example, while the majority of the index criteria objectively could be fulfilled within a higher maturity stage, some aspects were not fulfilled in lower stages, based on collected data, which meant that an organization’s maturity could span over three different stages. In these occurrences, the organization was allocated to a lower maturity stage. With another classification lens, it could be argued that the organizations have a higher or lower maturity, than other organizations allocated to the same stage.

In line with Teichert (2019), this issue can arise because there is no harmonized definition of AI maturity, digital maturity or digital transformation and the impact each has on business model innovation. This reinforces the critique against maturity models and emphasizes that the framework should rather be seen as a guideline for which areas to work on, rather than facts.

Furthermore, the paper found that the framework lacks direction and criteria for what to base the classification on to gain a coherence between the different aspects within and between maturity stages. Therefore, the index could be improved by integrating how to relate to metrics for AI maturity. It can help organizations to benchmark their current maturity level compared to other organizations. In addition, specific AI metrics could be further integrated into the framework.

Additionally, the framework lacks clarification of the depth of the scope depending on organizational size, e.g. a single organization, an entire group or an ecosystem of mutual partners. The framework further does not clarify if the index considers differences between public and private companies, and if there should be due to their different organizational purpose, which could be beneficial to integrate to provide clarity.

Furthermore, we found that the index loosely mentions trustworthy integrated AI as the core of the framework, but lacks clarification to the extent of how these aspects affect each dimension in the framework.

6.3 Making AI valuable

The response from respondents aligned well with previous research on what makes AI valuable, namely the power it has to process “big data” at an extremely fast pace (Iansiti & Lakhani, 2020; Sharda et al., 2014; Loebbecke & Picot, 2015). There is consensus among respondents that data is the main component for scaling AI. Without data, there is no fuel to feed the AI model with (Yams et al., 2020).

However, most respondents point out that it is possible to scale AI even if there is only a small amount of available data. The respondents believe that organizations need to look at the data in relation to the purpose the AI model is supposed to solve. Available data may be sufficient to meet a limited scope, or one may have to adjust the scope according to what data is available. The respondents highlight that in the beginning it is not a requirement to have a large amount of data to integrate AI with the business model. However, there will be more possibilities for what the organization can do with the AI model when it has access to a larger amount of data points and a better quality of that data. Additionally, according to Respondent 4 there are opportunities for an organization to accelerate and facilitate the use of existing data. For example, Respondent 4 points out that one success factor was to increase qualitative data by labeling it themselves. In this case, the organization could train its AI model faster.

Data management or having an infrastructure that is preferable for further scaling of AI does not seem to be a decisive factor in the short term based on the result. Companies can use technical infrastructure from larger platforms. However, that companies must re-architect their operating model to break silos and generate higher business value eventually, does plenty of the respondent state which is aligned with previous research by Iansiti and Lakhani (2020). Further, an enabling factor when implementing necessary re-architectures for a shorter purpose is to choose cloud solutions. The respondents suggest that that is a way to come around legacy from previous infrastructure investments in an easier way. Even if subscriptions to different platforms can cost on a monthly basis, creation of new legacy can be avoided by avoiding major infrastructural investments in technology that is not relevant or will be less efficient in the long run.

Judging by the respondents' answers, an important factor is that the specific AI implementations are aligned with the overall business strategy and that it generates a rapid effect for a specific business value/problem. Similarly to what Yams et al., (2020) emphasis in the AIMI strategy dimension, it is important to align AI with the broader business context. Further, this is in line with Fountain - Jones (2019), who suggests that organizations fail to scale because of the tendency to focus on specific technical aspects or how to store data. Instead of the actual business value to be generated with AI. It further aligns with Heukamp (2020), who suggests that being able to ask the right questions is important, because leaders will make decisions based on output from the AI model. Furthermore, it is in line with how Marr (2019) argues that without thinking of strategic questions, organizations waste money and time on cognitive technology and loosely experimenting with AI will not necessarily generate the intended effects on profitability.

Another aspect of being able to ask the right questions and understand the context of data and output from the AI model increases the chance of developing trustworthy integrated AI. Based on the findings, trustworthy integrated AI does not necessarily need to be considered to technically scale an AI solution, but, if organizations want to be perceived as a serious actor on the market, there are expectations of adopting certain guidelines in regard to AI. This means not only living up to legal requirements for data collection and data management, but is taking cybersecurity aspects into account and continuously raising issues such as ethics and potential bias to avoid unpleasant consequences. All respondents emphasized that they take these aspects into consideration when scaling AI, which is aligned with EU’s guidelines to AI, based on a strong ethical framework (Annoni et al., 2018).

Furthermore, the findings suggest that it is important to have a clear focus. Not on a specific technology, but rather on a specific problem or value that the AI model aims to solve.
It further points out the importance of a permissive mindset where experimentation is encouraged. This further aligns with what Mohanty & Vyas (2018) suggest in their research, that by allowing experimentation an organization can develop an ability of learning by failing fast. In this way, the organization does not bleed unnecessary resources on AI pilots which does not fulfill a business need, which Respondent 3 mentions.

In order to create a mindset of experimentation, the findings suggest that leaders need support by management and preferably a centrally made decision to invest in AI. There needs to be an intent to invest. However, it does not mean the management needs to be involved in the actual deployment details, as it may lack in-depth knowledge which causes unrealistic expectations of the result. However, based on the findings, it seems important that the team involved has a certain type of mindset that the leader helps to shape. It is in line with Heukamp (2020), which suggests that having leaders with an inclusive leadership style, which provides transparency, communication and adaptability are useful for facilitating an environment for AI development, as well as adopting agile development methods.

It should be mentioned that it is possible to scale a first use case even if the entire organization is not on the same track or has a data-driven organizational culture that permeates the entire organization. But for continued integration of AI, data management and a data-driven organizational culture are important aspects, according to multiple respondents. Which is in line with existing research by McAfee and Brynjolfsson (2012) and Iansiti & Lakhani (2020).

Moreover, that certain skills are needed to be able to scale AI is important, according to the respondents. But as long as there are strong business skills and a basic AI understanding most consulting firms can contribute with niche expert skills. This is in line with Iansiti and Lakhani (2020), who suggest that demonstrating the value of analytics based decision-making can be done by vendors or consultants without large organizational or cultural shifts.

There was no coherence among the respondents when it comes to criteria for scaling a POC, but it was important to prove business value at an early stage. This was most easily done by scaling the use case into small parts with little impact on the organization. This aligns with how Yams et.al (2020) describes "bolt-on" application of AI, with an intent of streamlining existing processes, rather than radical AI integration of new business models. It further aligns with Günter et al., 2017, who suggests that compared to digitally born startups, which can take advantage of low entry barriers and more easily set up new data-driven business models without previous legacy. Incumbent organizations have to rethink how data affects existing business models and leverage data for incremental business model innovation. The organization makes small adjustments to existing processes but continues to function “as usual” in a more efficient way than previously.

Furthermore, the findings also suggest that the more “AI-mature” an organization is, the more inclined it is to realize both incremental and radical innovation. This is aligned with Yams et al., (2020), which suggest that organizations need to move towards the Inquiring and Integrated stages in order to start increasing incremental innovation and strengthening their organizational capacity for more radical innovation enabled by AI.

6.4 Further integration of AI

However, for incumbents to leverage data for a more radical business model innovation and *new* value propositions, the findings suggest that the organizations must use available resources to build certain in-house capabilities in order to move from one stage of maturity to another, which aligns with Günter et al (2017).

The findings suggest that if the organization has an ambition to become an "AI factory" in the long term and truly integrate AI with its core business, investments are required in a foundational in-house capability to set the right requirements for AI solutions.

In order to move towards AI integration with core business models, the organization needs to review its data flows and not only consider volume but further consider velocity and variety of data, in order to increase access to qualitative data in real time. This requires a certain type of “data management maturity” and having the ability to identify relevant information as data points, to collect, analyze and use in the business. The findings further suggest that it is beneficial to look beyond the organization's internal processes, to combine its own data sources with external data sources.

Moreover, in the long term, there is an advantage of owning all or parts of the technical infrastructure to develop and maintain AI solutions. Although on-premises solutions can generate higher costs in the form of hardware and software licenses and certain expertise to maintain, it does provide greater flexibility and control over the data, which is in line with how Iansiti and Lakhani (2020) and Nakkeeran et al. (2021) describe the pros and cons between on-premises and cloud solutions.

Furthermore, there are several reasons to invest in building internal AI capabilities to gain a long term competitive edge and flexibility to design the solution according to the organization's specific conditions. In the majority of use cases, the findings suggest that there is a certain degree of anxiety among organizations about falling behind and losing market shares by not building their own AI solutions and growing AI capabilities. However, the rapid technical development in AI makes it challenging to transfer expert competences from consulting firm to customer and fully take over operation and development. It creates a mutual dependency on access to expert competence and the technical platform on which the solution lies.

The findings further indicate that inclusion in an ecosystem could be a cost-efficient way to gain access to data and talent. Inclusion in a wider ecosystem does not necessarily need to be where organizations start their AI journey, but if they want to take a leading position for AI development in their ecosystem, it is important to build mutual relationships with external parties. An innovation perspective can be important, to identify potential AI use cases together with partners for business model innovation through ecosystem orchestration.

To be able to navigate in a complex, external environment, the findings suggest that an open and humble mindset, together with a certain degree of AI experience can benefit and build trust among parties, providing access to talent and opportunities for sharing resources. This aligns with how Ricart (2020) describes the growth of ecosystems as a business model trend, where organizations share value creation and capture over a network of complementary products and services, purchasing and providing different solutions from and to other members of the ecosystem.

Moreover, involvement in an ecosystem for AI development places higher demands on leaders' ability to lead change management initiatives within the organization and with external parties. This aligns with Heukamp, (2020) suggestion that leaders need change management and coaching skills to facilitate interaction between humans and machines to establish a culture of collaboration around AI-driven projects. Furthermore, this type of collaborative and data-driven mindset should permeate the entire organization, to encourage a data-conscious culture suited for AI integration.

Surprisingly, more than representing trusted AI-partners to their customers, the respondents had little to share on the ecosystem dimension. Consequently, the findings’ indicate that the ecosystem dimension does not seem to be the primary dimension for organizations to start investing in to enhance the organizations' development towards integrated AI. In line with Yams et al. (2020) maturity stages, this dimension seems to be more vital to invest in at a later maturity stage of an organization's AI journey and therefore not the priority for unexperienced organizations with a lower degree of AI maturity. However, it is a possibility that another phrased interview guide or a different selection of respondents could have provided different answers.

Furthermore, the paper managed to retrieve little data within resistance to change due to AI deployment. However, the respondents indirectly reasoned about how to avoid resistance. The respondents had an open discussion during the interviews about strategic and tactical aspects, which they took into consideration while planning for the deployment to reduce the risk of resistance. Moreover, the respondents mentioned reflecting on change management before deployment as a success factor for AI deployment. Two primary tactics were expressed. Firstly, to choose an initiative which has a small impact on the organization and where few employees are affected by the change. Secondly, to start small and prove the value of the AI solution to build trust for AI solutions and thus enhance the conditions for further improvements and deployment of initiatives with a bigger impact on the organization.

Lastly, it is even more important that the ownership of the AI solution is placed with business operations, rather than the IT department. And also to align AI objectives with overall business strategy, which are in line with how Fountain-Jones (2019) describes IT-business alignment. Therefore, it is crucial that the organization has made a central decision to invest in AI and develop processes for prioritization among use cases.

7. Conclusion

The paper sought out to answer the *research question: Which prerequisites are vital for organizations when integrating AI for business model innovation?*

To move from POC/pilot to scale a first AI use case, the findings suggest that access to a certain amount of data is essential. Organizations further need an understanding of AI. However, they do not need to have required expert competences for developing and maintaining AI-models or the technological infrastructure in-house, these aspects can be provided by vendors. What is fundamental however, is to involve business experts and that the AI deployment focuses on achieving a specific business value. Moreover, there must exist an intent to experiment with AI and an experimental, permissive organizational culture with a clear result focus. Furthermore, it is important that there is a centrally made decision from management to scale AI. A specific success factor has been to start small and scale the AI solution in several steps, and prioritizing use cases which provide large value with a small impact on the organization.

For continued AI integration, it is even more important that there is a centrally made decision from management to invest and that AI strategy is aligned with overall business purposes. Especially if the organization has an ambition to take a leading role in its ecosystem and integrate AI for a more radical innovation of business models. Moreover, a more qualitative and varied amount of data and data management ability is required. It is beneficial to invest in in-house competencies and to review alternative infrastructure investments. Both on-premises and cloud solutions can be used, but there are clear advantages from choosing cloud. AI integration involves re-architecture of the organization itself. It is an ongoing journey that requires moving from siloed data to becoming a data-hub, the last stage before turning into a fully functioning AI factory. The organization will start to understand that it will need to change existing processes, leaders will need support to initiate change management actions since this stage can be met with resistance when bringing the entire organization on track. Also establishing a data-driven culture that welcomes ideas from different parts of the organization and encourages further collaboration with ecosystem partners is needed to gather cross-fusions and cost sharing. Lastly, regardless of scaling a first or a large portfolio of use cases, it is important to consider trustworthy integrated AI as a core aspect for integration, to be seen as a serious actor on the market. Furthermore, it can be beneficial to quantify risks and rewards with AI applications to measure progress and set reasonable criteria for following-up on business model innovation.

7.1 Future research

As mentioned in the research gap, Artificial Intelligence (AI) is still largely unexplored within information systems research and most published work remains non-academic (Collins et al., 2021). The paper encourages further academic and hybrid contributions to the AI research field.

While the paper has provided some insight to a number of success factors for scaling AI use cases, future research could continue to explore how higher levels of AI maturity affects AI application with a more “radical” innovation focus of business models, and compare this to traditional innovation management processes. As previous research mainly focuses on scaling AI for “bolt-on” efficiency gains of *existing* business models, it could be beneficial to further explore AI in relation to business creation, i.e. *new* business models. While the study has provided some insight to how organizations should develop their digital business strategies by incorporating AI for business creation, the paper encourages further research on this topic by e.g. comparing digitally-born, AI-first organizations with incumbents.

The paper further identifies a need for more research on ecosystem collaboration, especially for how to access and share data, algorithms, infrastructure, talent and lessons learned among trusted partners.

While the study has provided insight to different types of AI applications, future research could explore benefits between AI methods for specific AI application, compare expectations of business value between specific technologies and how business value of specific use cases evolves over time (Collins et al., 2021).

Lastly, to be able to quantify business value and compare it between applications, the paper proposes further research into relevant criteria/metrics for scaling and measuring AI performance over time.

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9. Appendices

Appendix A. Interview guide in English

Case specific questions

- Can you shortly describe the AI initiative that was implemented and its scope?
- What was the main purpose with the initiative?
- Where did the initiative come from? (internally/externally)
- Did the initiative have a clear sponsor? a business/product owner?
- Who were key stakeholders of the initiative?
- How was the AI method/solution tested? (Proof of concept phase)
- Moving from the POC phase to scaling up the initiative, what was the most important criteria(s) to continue with scaling?
- How did the organization measure success / failure of the initiative?
- What are the results of the initiative so far?
- Which parts of the organization led / were a part of the deployment?
- How was executive management involved and which role did they play for the initiative's success/shortcomings?
- Which resources were allocated ? (human, financial, time..)
- What competencies existed/were lacking to complete the deployment?
- Was any specific project management methodology used? (waterfall / agile)
- Was consideration to safety (cyber security) or ethical aspects important when implementing the AI initiative ?
- Did the implementation affect the way of working for employees and if so in what way?
- Did the implementation require adjustments in the infrastructure?
- Which part(s) of the organization cater the maintenance and continued improvement/development of the initiative?

Strategy

- Does the organization have a written AI vision?
- Does the organization have an AI strategy and/or roadmap?
- Does the organization have an AI portfolio? (are there more than one AI initiative in the pipeline?)
- Does the organization have a process for finding suitable AI use cases?

Mindset

- How would you describe the organization’s organizational culture when it comes to data?
- How would you describe the organization’s balance between efficiency and innovation efforts?
- How involved are employees in AI initiatives and contributing with ideas for venting/further development?
- How would you describe organization leaders and executive management's view on AI?

Organizational

- Does the organization have an AI team?
- How would you describe the organization’s alignment between IT/digital department(s) and the core business?
- Do you know if the organization conducts any type of training for their employees around AI?

Data

- Which type of data and from which data sources does the organization collect data? (photos, text, sensor input etc.)
- How does the organization ensure data quantity, quality and compliance with eg. GDPR?

Technology/Infrastructure

- How does the organization store and analyze data?
- Does the organization have an infrastructure which enables scaling up AI deployments?
- Does the organization have AI-related documentation, algorithms, data pipelines or infrastructure available via a central platform so that it can be reused for future applications?
- Do you consider legacy from previous infrastructural investments to be a disadvantage to scaling AI initiatives?

Ecosystem

- How does the organization view developing AI solutions together with external partners?
- Which role does the organization intend to have in its broader ecosystem when it comes to AI? (with customers, suppliers, partners, agents, consumers)
- Does the organization have a process for deciding whether to make their own or buy ready solutions for different AI use cases?

10. List of figures

Exhibit 1.

	AI taxonomy	
	AI domain	AI subdomain
Core	Reasoning	Knowledge representation
		Automated reasoning
		Common sense reasoning
	Planning	Planning and Scheduling
		Searching
		Optimisation
	Learning	Machine learning
	Communication	Natural language processing
	Perception	Computer vision
		Audio processing
Transversal	Integration and Interaction	Multi-agent systems
		Robotics and Automation
		Connected and Automated vehicles
	Services	AI Services
	Ethics and Philosophy	AI Ethics
		Philosophy of AI

Figure 1. AI taxonomy by the European Commission (Annoni et al., 2018)

Exhibit 2.

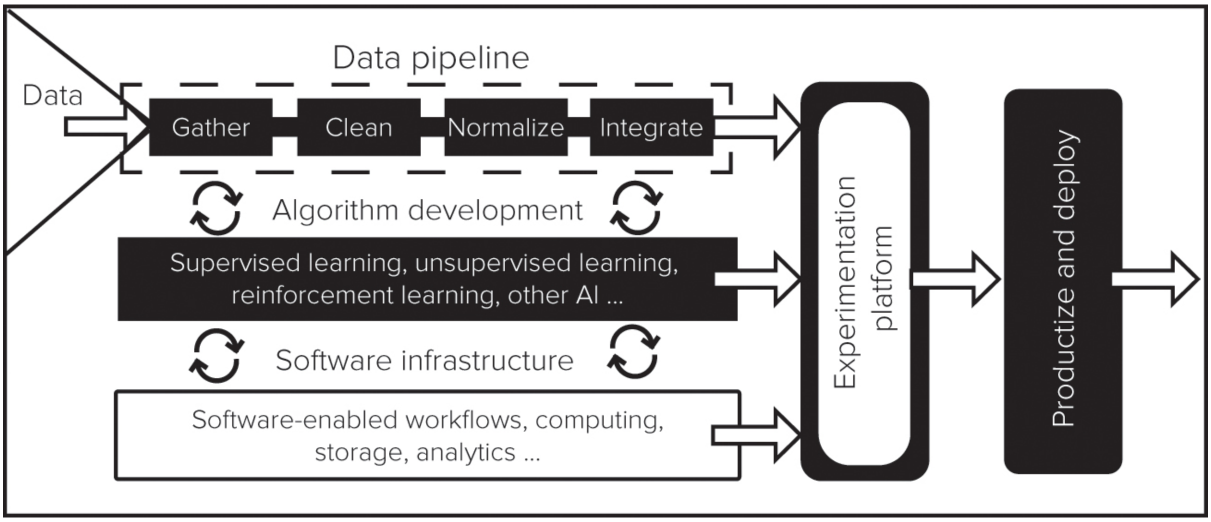

Figure 2. AI factory components (Iansiti & Lakhani, 2020)

Exhibit 3.

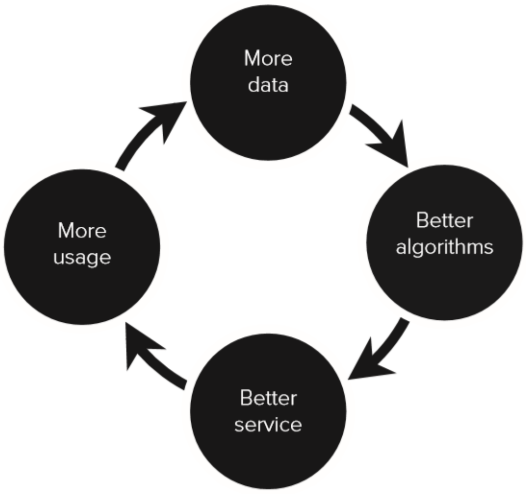

Figure 3. The AI factory's virtuous cycle (Iansiti & Lakhani, 2020).

Exhibit 4.

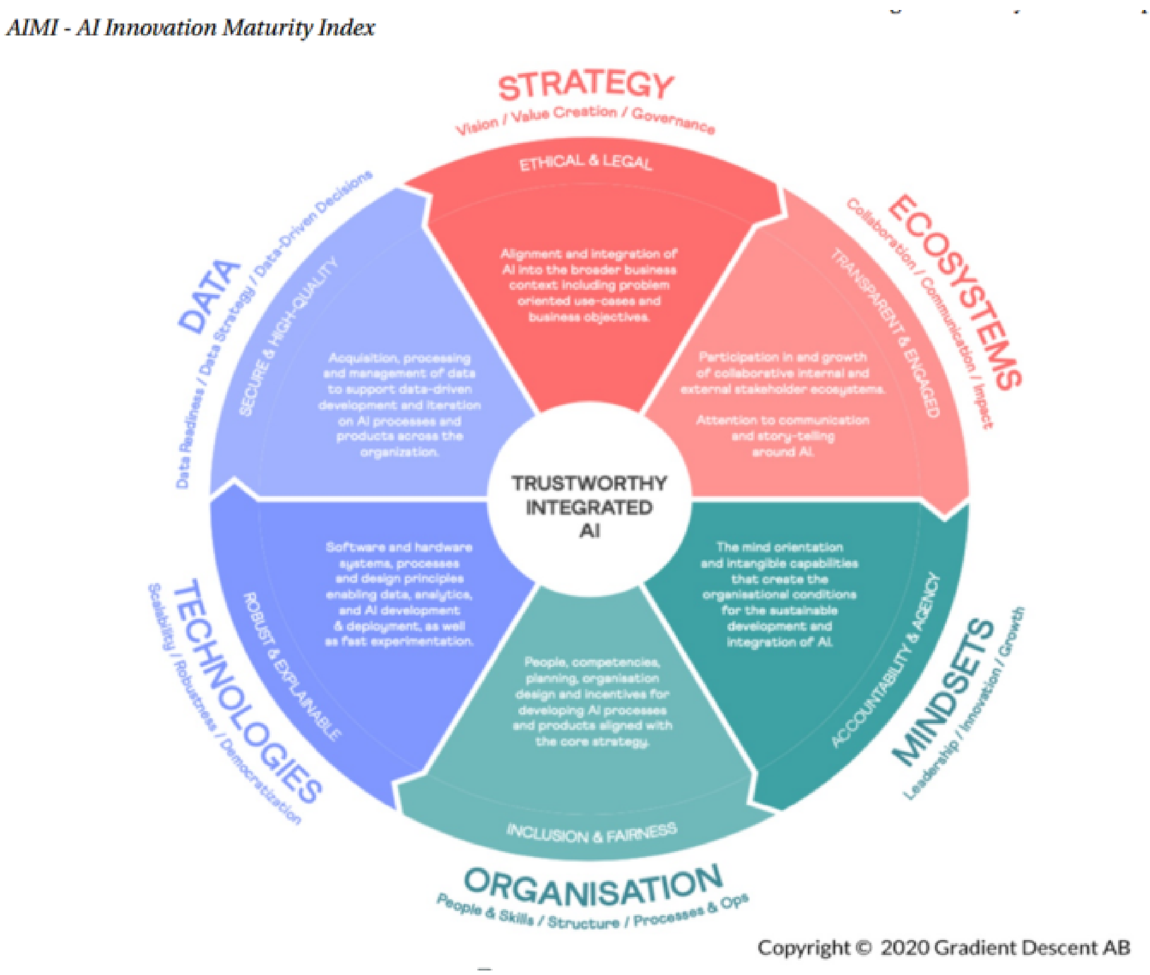

Figure 4. (Yams et al., 2020)

11. List of Tables

Table 1.

AI	Artificial intelligence
POC / POV	Proof of concept / Proof of Value
SME	Small and medium-sized enterprises
AIMI	AI Innovation Maturity Index
EU	European Union
ML	Machine learning
NLP	Natural Language Processing
MVP	Minimum Viable Product

Table 1. List of terms

Table 2

Organization A Consultancy firm based in Stockholm (HQ), Sweden **Case 1**	The firm offers clients services to identify how machine learning is or could be central for their clients to operate, compete and create value. Its services range from advisory projects and feasibility studies to end-to-end development and refinement of machine learning systems and products. It delivers solutions within multiple business areas within machine learning.
Organization B Organization based in Stockholm (HQ), Sweden **Case 1**	A leading technical distributor of installation products, tools, machines and services for professional users in the Nordic region.
Organization C Consultancy firm based in Gothenburg (HQ), Sweden **Case 2**	A data science supplier which offers optimization and automatization services. It delivers customized services within AI, data science and crawling built upon text, speech, images or traditional numerical data. Has its own data science framework.
Organization D Consultancy firm based in Stockholm(HQ), Sweden	Creating AI related solutions for clients through its software platform

Case 3	
Organization E Organization based in Gothenburg (HQ), Sweden **Case 4**	A world-leading manufacturer and provider of transport solutions
Organization F Consultancy firm and AI product organization based in Malmö, Sweden **Case 5**	Provides consultancy services and AI products to industrial companies to improve operations by using AI and ML technology.
Organization G Consultancy firm based in Gothenburg (HQ), Sweden **Case 6**	Provides strategic advice and tactical decisions, development and implementation of data strategy, analytics and AI
Organization H (Sponsor) Swedish national center for applied artificial intelligence, based in Gothenburg (HQ), Sweden	Its mission is to accelerate the use of AI for the benefit of Swedish society, competitiveness and to improve the quality of life for people living in Sweden. It runs projects of national interest and provides infrastructure in terms of personnel, know-how, hardware and targeted training for partners and the public. It has a data factory which enables partners to make data available and access data, make use of computing power and access storage capacity to realize AI projects. It aims to contribute to a culture of sharing, cooperation, and action within the Swedish AI-ecosystem and to accelerate applied AI in Sweden through partner collaboration.

Table 2. Overview of each organization involved in data collection

Table 3

Respondent	**Organization**	**Role**	**Process**	**Date**	**Language**
Respondent 1 Case 1	Organization A	*Consultant*	Semi-structured interview, digital.	16/03/22	Swedish
Respondent 2 Case 1	Organization B	*Head of labs and applied AI*	Semi-structured interview, digital.	20/04/22	Swedish
Respondent 3 Case 2	Organization C	*Consultant*	Semi-structured interview, digital.	23/03/22	Swedish

Respondent 4 Case 3	Organization D	*Consultant*	Semi-structured interview, digital.	25/04/22	Swedish
Respondent 5 Case 4	Organization E	*Product Owner*	Semi-structured interview, digital.	07/04/22	English
Respondent 6 Case 5	Organization F	*Consultant*	Semi-structured interview, digital.	08/04/22	Swedish
Respondent 7 Case 6	Organization G	*Consultant*	Semi-structured interview, digital.	20/04/22	Swedish

Table 3. Display of interviews.

Table 4

Use Case	Summary	Aim
Case 1 (Respondent 1 + Respondent 2) Industry: Retail	Developing a recommender system for website and app	Increase sales and customer satisfaction aspects
Case 2 (Respondent 3 with medicine organization) Industry: Pharma	Partly automatic trading of generic medicines	Replacing manual analytics tasks
Case 3 (Respondent 4 with architecture firm) Industry: Infrastructure	Identifying errors in infrastructural designs	Replacing parts of the manual quality control process
Case 4 (Respondent 5 with the help of various consultants) Industry: Heavy machinery	Predictive Maintenance of vehicles	Estimating time-to-failure for a product to enhance service offering
Case 5 (Respondent 6.AI with large manufacturing organization) Industry: Manufacturing	Using data analysis on manufacturing process	Improving product quality

Case 6 (Respondent 7) Industry: Financial services	Resource planning	Predicting staffing needs and removing manual planning tasks

Table 4. Use cases

Table 5

Maturity stage Use case	Foundational	Experimenting	Operational	Inquiring	Integrated
1			X		
2	X				
3		X			
4				X	
5	X				
6		X			

Table 5. Classification of Cases Overview matrix